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# Influencer Marketing Effectiveness

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# Influencer Marketing Effectiveness


## Abstract

Influencer marketing initiatives require firms to select and incentivize online influencers to engage their followers on social media in an attempt to promote the firms' offerings. However, limited research considers the costs of influencer marketing when evaluating these campaigns' effectiveness, particularly from an engagement elasticity perspective. Moreover, it is unclear whether and how marketers might enhance influencer marketing effectiveness by strategically selecting influencers, targeting their followers, or managing content. This study draws on a communication model to examine how factors related to the sender of a message (influencer), the receiver of the message (influencer's followers), and the message itself (influencer's posts) determine influencer marketing effectiveness. The findings show that influencer originality, follower size, and sponsor salience enhance effectiveness; posts that announce new product launches diminish it. Several tensions arise when firms select influencers and manage content: Influencer activity, follower–brand fit, and post positivity all exert inverted U-shaped moderating effects on influencer marketing effectiveness, suggesting that firms that adopt a balanced approach along these dimensions can achieve greater effectiveness. These novel insights offer important implications for marketers designing influencer marketing campaigns.



***Keywords:*** influencer marketing effectiveness, online influencers, consumer engagement, social media, marketing strategy

Consumers' growing skepticism toward traditional marketing has made it increasingly difficult for firms to attract and influence consumers. Many marketers turn to online influencers to promote their brands and products on social media (e.g., Instagram, Facebook, Weibo), propelling the growth of *influencer marketing*, a communication strategy in which a firm selects and incentivizes online influencers to engage their followers on social media in an attempt to promote the firm's offering (Leung, Gu, and Palmatier 2022). The firms select and pay (e.g., pay-per-post) online influencers—individuals, groups of individuals, or even virtual avatars who have built networks of followers on social media (De Veirman, Cauberghe, and Hudders 2017). Although some influencers build such a large following that they attain celebrity status, they differ from celebrities in the source of their fame. Whereas celebrities have succeeded in some credentialed, institutional setting (e.g., acting, music, sports), influencers are not certified by formal institutions (McQuarrie, Miller, and Phillips 2013). They accumulate followers by sharing content and weave brand endorsements into their personal stories and posts, resulting in content that appears authentic and provides consumption value (Lou and Yuan 2019).

Over 75% of marketers intend to dedicate resources to influencer marketing, with related spending expected to reach $16.4 billion by 2022 (Influencer Marketing Hub 2022). However, industry reports predict "there are disappointed marketers out there spending budgets but not really knowing what benefit the campaign has brought them" (Brennan 2019). Influencer marketing requires a lot of resources but also is difficult to implement and assess, making it critical to identify the decision criteria that firms can use to enhance the effectiveness of their influencer marketing efforts. According to emerging research, certain features of influencer marketing, such as source and post characteristics, affect outcomes such as consumer engagement (Hughes, Swaminathan, and Brooks 2019; Valsesia, Proserpio, and Nunes 2020), brand and influencer attitudes (De Veirman, Cauberghe, and Hudders 2017; De Veirman and Hudders 2020), purchase intentions (Lee and Eastin 2020; Lou and Yuan 2019), and product sales (Bharadwaj et al. 2022). However, few studies explicitly assess *influencer marketing effectiveness* in terms of engagement elasticity, defined as the percentage change in consumer engagement due to a 1% increase in influencer marketing spend.[1] This gap might reflect the lack of access to influencer cost data, but ignoring such costs hinders any accurate evaluation of the effectiveness of marketing spending. As influencer marketing becomes increasingly competitive, firms' ability to allocate their budgets optimally, by selecting individual influencers and managing individual posts in ways that maximize engagement elasticity, can establish their competitive advantages. We thus gather influencer cost and engagement data, and undertake a systematic assessment of influencer marketing effectiveness across varied conditions.

The conceptual framework we propose for doing so reflects communication models (Lasswell 1948; Shannon and Weaver 1949) and their component characteristics, related to (1) the sender of a message (influencer in our research context), (2) the receiver of the message (influencer's followers), and (3) the message itself (influencer's marketing post). Specifically, we investigate whether selecting influencers who post more or fewer posts (*influencer activity*), provide original content (*originality*), or have more or fewer followers (*follower size*); targeting follower networks with different levels of *follower–brand fit*; and posting content with distinct degrees of *post positivity* and *sponsor salience*, or content that relates to *new product launches*, moderate engagement elasticity (see Figure 1).

[Insert Figure 1 about here]

[1] We use *influencer marketing effectiveness* and *engagement elasticity* interchangeably to refer to the main effect of influencer marketing spend on consumer engagement. In the conceptual framework, we detail factors that moderate this main effect (Figure 1).

Based on this framework, we derive two research questions:

(1) Does consumer engagement increase in response to influencer marketing spend?

(2) Can marketers enhance engagement elasticity by strategically selecting influencers and their followers, as well as managing their content? That is, how do influencer-, follower-, and post-related factors interact with influencer marketing spend in affecting consumer engagement of the sponsored post?

To address these questions, we obtained data from a large influencer marketing platform ("Data Provider") that allows firms to select and pay online influencers to share sponsored posts about their brands and products on various social networks. We gather rich data about sponsored posts, which appeared on a prominent social network and were transacted through the Data Provider in October 2018; the gathered information includes each post's sender (i.e., influencer), receiver (i.e., followers), and message characteristics. This data set is unique in several ways, relative to the data that support prior studies (e.g., Hughes, Swaminathan, and Brooks 2019). It features a more diverse group of online influencers, spanning a broader range of campaigns, brands, and categories (i.e., 5,835 influencer marketing posts related to 1,256 campaigns written by 2,412 influencers, sponsored by 861 brands in 29 categories). With access to influencer cost data for each post, as well as 24-hour lagged engagement data (e.g., number of reposts), we can estimate influencer marketing effectiveness in terms of engagement elasticity, establishing the incremental contribution that influencer marketing spend makes for fostering engagement.

This research contributes to extant literature in several ways. First, as mentioned, recent studies note various consumer and firm outcomes of influencer marketing (e.g., Bharadwaj et al. 2022; Hughes, Swaminathan, and Brooks 2019) (Table 1), but most of them do not account for the costs of generating those outcomes. As Batra and Keller (2016, p. 136) argue, "marketers must evaluate marketing communications … against their cost to arrive at the most effective and most efficient communications program." Therefore, this study empirically examines the effectiveness of influencer marketing spend (i.e., pay-per-post) for generating consumer engagement, as measured by engagement elasticity. Our results reveal that increasing the influencer marketing budget can increase consumer engagement: *Ceteris paribus*, a 1% increase in influencer marketing spend increases engagement by .457%. By assessing and comparing influencers' engagement elasticities and base engagement levels, we also establish how firms can allocate their budgets optimally. On average, the firms in our data set could increase consumer engagement by 16.6% if they allocated their budgets proportional to these elasticities and base engagement levels, rather than their current allocations.

[Insert Table 1 about here]

Second, we apply a communication model (Lasswell 1948; Shannon and Weaver 1949) as an alternative to the theories adopted in prior research (Table 1), which offers a more comprehensive assessment of how factors related to the sender (influencer), receiver (followers), and message (influencer marketing post) lead to varied influencer marketing effectiveness. These categories of factors are central to campaign designs, which generally require selecting effective influencers and follower groups to target, as well as defining effective posts. Selecting influencers who transmit more original posts, relative to posts created by others, and with larger networks of followers, along with incorporating more clickable mentions and links in the sponsored posts, enhances effectiveness. Sponsored posts that announce new product launches diminish effectiveness, due to the potential risks and advertising clutter involved with new products. This overarching communication model also sheds new light on follower–brand fit, a relatively less studied receiver factor, and reveals the promising potential of leveraging big data to make effective targeting decisions (Nelson and Webster 2016).

Third, influencer marketing agreements empower influencers to transmit brand-related information to target consumers, which differs from traditional brand- or user-generated content. This research establishes evidence of inverted U-shaped moderating effects of influencer activity, follower–brand fit, and post positivity. In turn, we suggest that firms should select influencers who display medium levels of posting activity rather than those who post too frequently. This insight also helps reconcile some mixed findings in previous studies (Stephen et al. 2017; Suh et al. 2010). A prevailing view in celebrity endorsement literature suggests that brand fit is a strong indicator of effective communication (Bergkvist and Zhou 2016), but we determine that followers with a high degree of shared interests with the brand may not be the best group to target with influencer marketing. Finally, adding nuance to previous literature that suggests positive content is more viral (Berger and Milkman 2012), our analysis indicates that a blend of positive and negative content can increase engagement elasticity by 5.6% (22.4%), relative to content that is one (two) standard deviation(s) higher in positivity. These nonlinear effects help clarify some unique tensions that arise in influencer marketing campaigns: Followers know influencers are paid, but influencers still need to appear authentic, display leadership, and provide communication value to those followers (Leung, Gu, and Palmatier 2022).

## Conceptual Background and Hypotheses Development

### *Influencer Marketing Effectiveness*

Considerable marketing literature deals with the effectiveness with which advertising can produce relevant firm outcomes such as sales, market share, and firm value (Dinner, Van Heerde, and Neslin 2014; Sethuraman, Tellis, and Briesch 2011; Sridhar et al. 2016). A conventional measure of advertising effectiveness is elasticity, defined as the percentage increase in an outcome variable when an input variable (e.g., advertising spend in a particular medium) increases by 1% (Danaher and Van Heerde 2018). Elasticity provides a suitable measure for gauging advertising effectiveness because it is dimensionless and can be computed for any outcome variable (Venkatraman et al. 2015). Prior studies that examine the advertising elasticities of various traditional (e.g., print, radio) and online (e.g., paid search, online display) advertising media also identify contextual factors that alter these elasticities (Becker, Wiegand, and Reinartz 2019; Datta, Ailawadi, and Van Heerde 2017; Van Heerde et al. 2013).

However, few prior studies account for the costs associated with online influencers to establish their effectiveness or elasticity. Therefore, we sought access to unique spending data for influencer marketing posts. Then, to reflect a primary objective of influencer marketing—namely, to encourage consumers' engagement with sponsored content on social media (Hughes, Swaminathan, and Brooks 2019)—we include engagement as an outcome variable. Broadly defined to encompass cognitive, emotional, and behavioral activities (Hollebeek, Glynn, and Brodie 2014), engagement on social media can be operationalized as a set of measurable consumer behaviors in response to online content, such as liking, commenting, or reposting content (Malhotra, Malhotra, and See 2013). These forms of engagement create ripple effects, influence other potential customers, and contribute to firm performance (Pansari and Kumar 2017). We prioritize the *number of reposts* an influencer marketing post generates, because reposting is a deeper form of engagement than just liking; it implies consumers self-select to propagate the content to their own networks (Malhotra, Malhotra, and See 2013).

### *Models of Communication*

Similar to other communication strategies, firms use influencer marketing to communicate and deliver value to consumers, in the pursuit of favorable firm outcomes (Leung, Gu, and Palmatier 2022). Yet instead of communicating directly with consumers, influencer marketing requires firms to empower influencers to create and transmit brand-related information through social media; this transmission is what determines the process of value communication specific to influencer marketing (Balducci and Marinova 2018), which also may align with traditional communication models (Lasswell 1948; Shannon and Weaver 1949) that depict processes by which messages flow from senders to receivers. The sender is the source of the message. The message, consisting of words, sounds, or behaviors, gets transmitted through a channel to a receiver, who is the audience. Most models thus cite three common elements that shape effective communication: (1) the sender of a message, (2) the receiver of the message, and (3) the message itself (Swani, Brown, and Milne 2014; Walker et al. 2017). The sender's characteristics indicate how believable or influential he or she is as a message source (Self 2009; Wilson and Sherrell 1993); receivers' characteristics determine how involved they will be with the message (Boerman, van Reijmersdal, and Neijens 2015; Eisend and Tarrahi 2016); and the message's characteristics denote its content value (Ducoffe 1996; Lou and Yuan 2019). Thus, all these factors can enhance or detract from the message's potential to elicit responses from receivers. Accordingly, we predict that characteristics pertaining to the influencer (sender), the influencer's followers (receiver), and the influencer's marketing post (message) function as moderators that lead to the varying effectiveness (i.e., engagement elasticity) of influencer marketing.

***Sender (Influencer) Characteristics***

Influencers are fundamentally content generators and disseminators on social media (Yuan and Lou 2020). Unlike firm-generated communications, for which firms send brand messages, influencer marketing empowers influencers to take on sender roles. Firms tend to select influencers on the basis of their posting behaviors, such as how frequently or what kind of content they tend to post, and their follower size. We accordingly examine how influencer activity, originality, and follower size, as sender traits, might moderate engagement elasticity.

*Influencer activity* refers to the frequency with which an influencer transmits content (e.g., messages, photos, videos) on social media (Stephen et al. 2017). When influencers post frequently, followers infer that the information sent by them is fresh and up-to-date (Stephen et al. 2017). Moreover, as influencers frequently post on social media, followers come to sense that they know the influencers intimately (Escalas and Bettman 2017), which enhances their trust in the influencer. An increase in spend on an influencer who posts more frequently should then generate more engagement, because the followers perceive him or her as an updated, trustworthy message sender and thus are more likely to respond (Wilson and Sherrell 1993).

However, if an influencer posts extremely frequently, the large volume of posts may distract followers and dilute their attention to any particular post (Gong et al. 2017). Posting too frequently also can clutter followers' feeds and create fatigue (Barker 2018). Followers then may grow uninterested in the influencer's posts, selectively filter them, or even feel annoyed by them, making the influencer a less effective message sender. These predictions suggest that, after an optimal point, an influencer with greater posting activity lowers the effectiveness of influencer marketing spend, because followers become less responsive to each individual post by that influencer. Whereas selecting an influencer who engages in minimal activity might not produce perceptions of credibility as a message sender, selecting one with excessive activity might backfire due to possible information overload. Therefore, we predict that influencer activity first strengthens the positive effect of influencer marketing spend on consumer engagement; yet, after reaching an optimal point, it starts to weaken the effect. That is, a moderate level of influencer activity is optimal for producing the highest engagement elasticity.

**$H_1$:** Influencer activity has an inverted U-shaped effect on influencer marketing effectiveness.

In managing their social media accounts, influencers post content written or produced by themselves or created by others. The tendency to post one type of content over another reflects *influencer originality*, defined as the degree to which online influencers create original content on social media and thereby achieve differentiation in followers' minds (Casaló, Flavián, and Ibáñez-Sánchez 2020). We expect it to enhance influencer marketing effectiveness for several reasons. First, original influencers produce content in their own words and style, which makes them stand out from the crowd of influencers in the market. Consumers like to talk or read about topics they find interesting or surprising (Moldovan, Goldenberg, and Chattopadhyay 2011), so influencers who offer greater originality should attract more attention than those with low originality. Second, influencers who share original content and ideas are likely to be perceived as knowledgeable, credible senders, with whom followers may prefer to interact (Ki and Kim 2019). Third, originality is a defining property of authenticity (Nunes, Ordanini, and Giambastiani 2021) and a key trait of successful influencers (Casaló, Flavián, and Ibáñez-Sánchez 2020). Original influencers use personalized methods to show how the touted product fits into their everyday lives, which consumers perceive as trustworthy (Leung, Gu, and Palmatier 2022). Overall then, original influencers may be more likely to be noticed and trusted by consumers, which make them more effective message senders. We expect influencer originality to positively interact with influencer marketing spend; that is, increasing the spend on original influencers should generate more engagement than on those who are less original.

**$H_2$:** Influencer originality enhances influencer marketing effectiveness.

*Follower size* refers to the number of followers an online influencer has on a social media platform (De Veirman, Cauberghe, and Hudders 2017). This characteristic provides an important criterion for selecting influencers, because it is easily observable on most platforms. Although most social network studies identify social hubs (i.e., well-connected people with many connections to others) as favorable seeding targets because their connectivity enables wider propagation and greater market size (Goldenberg et al. 2009; Hinz et al. 2011; Libai, Muller, and Peres 2013), it is unclear whether having more followers creates a stronger response to an increase in influencer spend on engagement. Some practitioners suggest that working with influencers with smaller followings is worthwhile because they may be perceived as more relatable and authentic (Hosie 2019); however, we posit that soliciting influencers with large follower size is effective for fostering engagement elasticity, for two reasons.

First, a large follower network grants an influencer access to a sizable pool of potential consumers and stronger potential for eliciting engagement responses. This is analogous to market entry contexts, where potential entrants often speculate that a large market size may offer them a better chance of success (Min, Kim, and Zhan 2017). Because having many followers grants an influencer greater potential reach, devoting more of the budget to collaborating with this influencer should generate more engagement and increase engagement elasticity. Second, more followers also evoke credibility. Follower size serves as a signifier of the influencer's popularity (De Veirman, Cauberghe, and Hudders 2017), status, and reputation (Labrecque et al. 2013). When an influencer has a large following, consumers likely believe the influencer is a valid and reliable message sender, ascribing greater opinion leadership and source credibility to her or him (Goldenberg et al. 2009). As a result, spending more to work with this influencer should be more effective, because consumers likely pay more attention to and more actively repost the content posted by a credible sender (Self 2009; Wilson and Sherrell 1993). On the basis of both reach and credibility effects, we expect that influencers with more followers are more effective message senders. Therefore, follower size should positively interact with influencer marketing spend to generate consumer engagement, prompting greater engagement elasticity for firms.

**$H_3$:** Influencer follower size enhances influencer marketing effectiveness.

***Receiver (Follower) Characteristics***

Firms also select influencers based on their followers' characteristics, according to whether those followers, as receivers of a sponsored post, are likely to find the content valuable and exhibit greater potential for engagement (Swani, Brown, and Milne 2014). Marketers often consider the composition of an influencer's follower network, so we focus on follower–brand fit to predict how it might lead to variations in influencer marketing effectiveness. *Follower–brand fit* is the degree to which the interests of an influencer's followers match with the domain of the sponsor brand. This fit would be high if, for example, a cosmetic brand were to work with an influencer whose followers are interested in beauty, medium if those followers like beauty and food, and low if they are interested only in food. In influencer marketing contexts, followers' digital consumer profiles provide a means for brands to engage in audience targeting (Neumann, Tucker, and Whitfield 2019). Firms can use consumers' viewing and clicking data to understand their interests almost instantaneously as they surf the Internet. As such, follower–brand fit is widely employed by influencer marketers (Hobbs 2019) and appears key to unlocking the potential of big data for improving marketing communications (Varnali 2021).

When a brand's domain aligns with the interests of the influencer's followers, a sponsored post about the brand is more personally relevant to those followers (Geng et al. 2021), which should motivate them to process the information (Petty and Cacioppo 1986). That is, these followers are relevant receivers to target, because they are likely to become involved with the post, evaluate it carefully, and determine whether and how to respond (Boerman, van

Reijmersdal, and Neijens 2015). Because follower–brand fit evokes followers' interests and draws their attention, an increase in spend on an influencer whose followers display high (vs. low) brand fit should elicit more engagement, leading to greater engagement elasticity.

However, if follower–brand fit is already high, increasing it further might backfire for several reasons. First, the influencer's followers already consume substantial social media content related to their own interests. If a post closely matches this interest, it competes for followers' attention with a clutter of other similar content (Nan and Faber 2004), which reduces the chances that it will be noticed or processed. Second, consumers become satiated with specific topics when the related content exceeds a certain level, after which they seek variety (McAlister 1982); if an influencer instead posts novel marketing information with some unmatched elements, it may break the monotony and draw followers' attention (Ordenes et al. 2018). Third, when consumers receive appeals closely matched to their interests, they may grow suspicious that the content is commercially motivated or manipulative. This growing suspicion can elicit consumer reactance (Campbell and Kirmani 2000), which likely hampers the effectiveness of the brand's influencer marketing spend. Therefore, we expect that followers with an intermediate level of follower–brand fit represent the optimal receiver group to target, because doing so leverages their shared interests but avoids information clutter, satiation, or reactance. We posit that follower-brand fit strengthens the positive effect of influencer marketing spend on consumer engagement up to a certain point, beyond which it starts to weaken the effect. Formally stated:

**$H_4$:** Follower–brand fit has an inverted U-shaped effect on influencer marketing effectiveness.

### *Message (Post) Characteristics*

Firms grant influencers a great deal of freedom to generate content, yet they still manage the content by providing briefs that outline the campaign's objectives or key messages (Leung, Gu, and Palmatier 2022). Thus, we investigate how firms may leverage post positivity, sponsor salience, and new product launch information to vary influencer marketing effectiveness.

*Post positivity* is the degree to which an influencer marketing post is positive (Berger and Milkman 2012). We anticipate an inverted U-shaped moderating effect on engagement elasticity. Any sponsored post likely is positive by nature (Haenlein et al. 2020), because positivity indicates the influencer's endorsement and persuasive attempt (Akpinar and Berger 2017). When an influencer endorses the brand, consumers anticipate that the offering has some valuable features that also may be worth sharing (Barasch and Berger 2014). Influencer marketing spend devoted to encouraging more positive posts thus should be beneficial, but we also note that the inherent features of influencer marketing might diminish these benefits if positivity builds beyond a certain point. Unlike organic recommendations, consumers know that influencers are paid to advocate for the brand. When influencers share highly positive comments about the brands they endorse (i.e., post positivity is very high), followers might question the extent to which their post is authentic (McQuarrie, Miller, and Phillips 2013) and instead perceive manipulative intent. Manipulative tactics can reduce perceived content value (Ducoffe 1996), activate consumers' persuasion knowledge, and elicit reactance (Campbell and Kirmani 2000). A moderately positive post that includes some negative comments should offer greater content value than posts with low or very high levels of positivity (Uribe, Buzeta, and Velásquez 2016), because it is positive enough to generate positive impressions but still allow for perceptions of discernment. We thus expect an increase in influencer marketing spend on moderately positive posts to produce the most engagement, resulting in the highest level of engagement elasticity.

**$H_5$:** Post positivity has an inverted U-shaped effect on influencer marketing effectiveness.

*Sponsor salience*, or the extent to which the sponsor brand is prominent in a post (Teixeira, Wedel, and Pieters 2010; Tellis et al. 2019), affects how consumers make inferences about the content. We operationalize it as the total count of sponsor brand-related mentions (or @s) and URL links and provide competing predictions on its moderating effect on engagement elasticity. According to conversational norms, contributions to a conversation should be informative (Grice 1975), and that norm should apply to influencer marketing too. Prior studies note the importance of online content's practical utility for encouraging engagement (Berger and Milkman 2012; Rooderkerk and Pauwels 2016). When the sponsor brand is prominent in a post, it offers important information to consumers that helps them comprehend and learn from the content (Teixeira, Wedel, and Pieters 2010). Influencer posts with higher sponsor salience are therefore perceived to be more informative and possess greater content value (Lou and Yuan 2019), and increasing spend to encourage such content should elicit greater consumer engagement.

However, there are also reasons to believe that sponsor salience may reduce engagement elasticity. The degree to which the sponsor brand is salient increases a post's commercialism (Tellis et al. 2019). The more an influencer's post links to the sponsor brand, the more it looks like a traditional advertisement and less like an authentic sharing from the influencer (Stubb 2018). Similar to intense branding activity in TV commercials, salient links to the sponsor brand makes a post seems too "hard-sell", which may annoy the consumers (Bruce, Becker, and Reinartz 2020; Teixeira, Wedel, and Pieters 2010). Increasing spend on such content should be less effective, suggesting that sponsor salience will negatively interact with influencer marketing spend in eliciting consumer engagement. Given the competing arguments on the moderating role of sponsor salience, we propose the following competing hypotheses:

> **$H_6$:** Sponsor salience (a) enhances influencer marketing effectiveness or (b) reduces influencer marketing effectiveness.

Finally, brands often solicit influencers to post about a *new product launch*. These posts are typically aimed at increasing consumer awareness about the new products and encouraging the spread of information on social media (Hughes, Swaminathan, and Brooks 2019). We expect that consumers should pay more heed to influencer posts introducing new products because they contain more novel and interesting information than those marketing existing products (Berger 2014). Prior literature suggests that new product advertisements are generally shared more because they make the sharers appear knowledgeable about the marketplace (Tellis et al. 2019). Accordingly, consumers in our study may more actively engage with or share new product launch posts to express their uniqueness or fulfill their socializing and helping motives (Berger and Schwartz 2011; Tellis et al. 2019), enhancing influencer marketing effectiveness.

However, new product launches also involve significant risks (Tellis et al. 2019); nearly 95% of them fail (Hyder 2019). Because consumers face uncertainty related to the performance, social desirability, and appropriateness of new products (Castaño et al. 2008), engaging with or reposting new product announcements might appear risky and contrary to their desire to avoid social disapproval (Berger 2014). In support of this reasoning, a study of Facebook advertisements (Gavilanes, Flatten, and Brettel 2018) reveals that people hesitate to share content about new products they have not yet experienced. An increase in spend on influencer posts that announce new product launches, relative to those that market existing products, should generate fewer engagement, because the heightened risks linked to new products likely reduce consumers' responsiveness to posts that feature such information. Due to the competing arguments, we offer the final set of competing hypotheses regarding the moderating role of new product launch posts:

> **$H_7$:** New product launch posts (a) enhance influencer marketing effectiveness or (b) reduce influencer marketing effectiveness.

## Data and Measures

### ***Data***

We test our framework using data obtained from a publicly listed influencer marketing platform in China (Data Provider). It helps brands select and pay online influencers to share posts about their products on various social networks; annually, it facilitates more than 120,000 influencer marketing post transactions. Data Provider shared data about its post transactions on Weibo (a popular microblogging site in China, similar to Twitter) with us. The data pertain to 5,835 influencer marketing posts written by 2,412 online influencers related to 1,256 campaigns for 861 brands in October 2018. The sponsor brands span 29 categories; the 6 largest are beauty products, e-commerce platforms, food and beverages, electronics, apparel, and personal care products. The unique data set includes each post's cost and 24-hour lagged engagement data (i.e., number of reposts and comments captured 24 hours after the post was shared on Weibo), so we can probe cost-based effectiveness in driving engagement. The substantial variance in size and focus of the influencers, their followers, and their posts support our analysis of contingencies.

### ***Measures***

Table 2 details the operationalization of the key variables that map onto our conceptual framework. Table 3 contains the descriptive statistics and correlations for the variables.

[Insert Tables 2 and 3 about here]

***Engagement.*** Following prior work (e.g., Valsesia, Proserpio, and Nunes 2020), we operationalize *engagement* as the number of reposts an influencer marketing post generates within its first 24 hours as our dependent variable. We use the 24th hour as a cut-off, in accordance with empirical evidence obtained from Data Provider that shows that activity largely halts after this point. In conversations with marketers, we learned that measuring engagement up to this point is consistent with industry standards. To confirm the robustness of the findings, we also use the number of comments as of the 24th hour as an alternative dependent variable.

***Influencer marketing spend***. Our focal independent variable is *influencer marketing spend*, or the monetary amount (in dollars) a brand spends on a sponsored post shared by an influencer. The payment is per post, as a one-off cost, such that the brand makes the payment to the influencer through Data Provider once she or he shares a post on Weibo. Some brands spend remarkable amounts (maximum of $92,857) on single posts, but the median amount ($293) suggests a reasonable budget. Due to substantial variation, we use a log-log model to estimate the effect of this variable on engagement, which yields a unit-free elasticity measure that accommodates potentially changing returns to scale and depicts the percentage change in engagement in response to a 1% increase in influencer marketing spend.

***Sender (influencer) characteristics***. *Influencer activity* is measured as the total number of posts (both sponsored and non-sponsored) an influencer published on Weibo in the 90 days prior to the campaign (Gong et al. 2017; Stephen et al. 2017). Higher activity implies that the influencer is a more active sender of information on social media. *Influencer originality* is the ratio of the number of original posts (i.e., both sponsored and non-sponsored posts written or produced by themselves) to the total number of posts an influencer published in the 90 days prior to the campaign. Greater originality implies that the influencer creates more original content, rather than transmitting content created by others. *Follower size* is the total number of followers (in millions) an influencer has on Weibo, prior to the campaign (Kupfer et al. 2018). It reflects the influencer's potential reach and perceived credibility.

***Receiver (follower) characteristic***. To measure *follower–brand fit*, we look at the degree to which the interests of an online influencer's followers match the associated domains of a post's sponsor brand. Weibo identifies users' interest(s) (e.g., travel, beauty, fashion, music) on the basis of their social media activities on the site. For each influencer, we obtained data on the number of followers identified as interested in each of the 42 domains prior to the campaign. Then, two independent coders coded whether a sponsor brand is associated with each of the same 42 interest domains (e.g., Lancôme is associated with beauty). The interrater agreement was 96.8%, and disagreements were resolved by consensus. The measure of follower–brand fit then is the percentage of an influencer's followers whose interests match the domains of the sponsor brand. Greater follower–brand fit indicates that a brand more accurately targets followers whose behavioral patterns (on Weibo) reveal interests that align with the brand's domains.

***Message (post) characteristics***. We measure *post positivity* as the ratio of the difference between positive and negative words to the total number of emotional words in an influencer marketing post [(number of positive words – number of negative words) / (number of positive words + number of negative words + 1)].[2] We conducted an automated sentiment analysis using a linguistic inquiry and word count dictionary to quantify the number of positive and negative words (Pennebaker et al. 2015). *Sponsor salience* is measured by the total count of @s to the sponsor brand's own Weibo account (e.g., @Dior, @KFC) and URLs linked to the sponsor brand's website or online shop in an influencer marketing post (Soboleva et al. 2017). Greater sponsor salience suggests a post has more direct links to the sponsor brand, which makes the sponsor brand more prominent. We used dictionary-based text analysis to code whether an influencer marketing post relates to a *new product launch*. Following Humphreys and Wang's (2018) procedures for the dictionary creation, dictionary validation, and post-measurement

[2] By adding 1 to the denominator (i.e., total number of emotional words), we ensure the inclusion of posts that contain no emotional words.

validation steps, we then applied the newly developed dictionary to a text analysis, for which a post is categorized as related to a new product launch if its content includes one or more words from the dictionary (= 1, otherwise 0) (see Web Appendix A1 for more coding details).

***Control variables***. We added a series of control variables that might influence engagement. At the post level, a dummy indicates whether an influencer marketing post is related to *promotion* (see Web Appendix A1), which is typically for encouraging consumer trial (Hughes, Swaminathan, and Brooks 2019). We also controlled for *post length*, measured as the total number of characters in a post. At the brand level, we controlled for *post number in campaign*, or the number of posts within an influencer marketing campaign launched by the brand. Brand type dummies indicate if it represents a *service (vs. product) brand*, *premium (vs. value) brand*, and *foreign (vs. local) brand* (see Web Appendix A2). To control for brand heterogeneity, we noted the fixed effects of *brand category*, using 29 categories (e.g., beauty products, e-commerce platforms, food and beverages, electronics, apparel, personal care). We also controlled for the effects of a holiday (i.e., Chinese *Golden Week* holiday in October) and *weekends*. Finally, we noted the influencer's *gender*. Alternative model specifications also allow for day-fixed effect and for influencer-level variation in both the intercept and slopes (see Web Appendices G and I).

## Model Specification and Results

### *Selection Model*

To obtain accurate estimates of the effect of influencer marketing spend on engagement (i.e., number of reposts),[3] we first addressed the potential for selection bias in our data. Certain influencers, due to their distinct characteristics, may be selected intentionally by brands to

[3] The main dependent variable is the *number of reposts* that an influencer marketing post generates within 24 hours. For a robustness check, we also consider the *number of comments* a post generates within 24 hours.

engage consumers. Therefore, we implemented a Heckman (1979) selection model to predict an influencer's selection, with a first-stage probit model specified as follows:

$$Pr(Selection_{jk} = 1 | \boldsymbol{X}_j, \boldsymbol{Z}_{jk}) = \Phi(\boldsymbol{X}_j\boldsymbol{\theta} + \boldsymbol{Z}_{jk}\boldsymbol{\eta}), (1)$$

where $j$ and $k$ denote influencer $j$ and brand $k$; $Selection_{jk} = 1$ (selection) or 0 (non-selection); $\Phi$ is the cumulative distribution function of the standard normal distribution; $\boldsymbol{X}_j$ is a vector of influencer-level variables that relate directly to an influencer's selection, including gender, follower size, and influencer activity; $\boldsymbol{\theta}$ and $\boldsymbol{\eta}$ are vectors of regression coefficients.

Furthermore, $\boldsymbol{Z}_{jk}$ in Equation 1 includes two control variables that affect a post's influencer selection but do not directly affect the engagement generated by a post, such that they satisfy exclusion restrictions (Gill, Sridhar, and Grewal 2017; Heckman 1979; Hughes, Swaminathan, and Brooks 2019). The first control variable is the selection of the second[4] most similar influencer (to a focal influencer $j$) by a brand $k$. Using the approach suggested by Hughes, Swaminathan, and Brooks (2019), we created an influencer-by-brand matrix (i.e., adjacency matrix reflecting the selection of influencer $j$ by brand $k$) and multiplied it by its transpose to derive an influencer-by-influencer matrix, whose off-diagonal elements indicate influencers who coappeared (i.e., selected by the same brand) most frequently. We then selected the influencer that is the second most similar to (i.e., coappears the second most frequently with) a focal influencer $j$ and used the selection (yes = 1, or 0 otherwise) of this "second most similar" influencer by brand $k$ as a control variable in $\boldsymbol{Z}_{jk}$. This control variable fulfills the relevance criterion (correlates with the selection of the focal influencer), because in practice, brands tend to

[4] We selected the second most similar (instead of the most similar) influencer to mitigate the possibility that the most similar influencer shares a large proportion of followers with a focal influencer, whose followers may coincidentally have seen a comparable post initiated by the most similar influencer and therefore have lower engagement with the post initiated by the focal influencer.

recruit influencers with similar characteristics (Hughes, Swaminathan, and Brooks 2019). It also meets the exclusion restriction, because even a similar influencer cannot directly affect second-stage engagement prompted by a post initiated by another (the focal) influencer. The second control variable in $\boldsymbol{Z}_{jk}$ refers to increasing (or decreasing) trends in influencer activity. Specifically, we calculated the time trend[5] of each influencer, based on posting activities in the past 90 days; this control variable satisfies the exclusion restriction. A brand manager might scan the historical posts of an influencer when making the recruitment decision, but second-stage engagement prompted by a focal post is unlikely to be influenced by prior posts.

Table 4 contains the estimation results of the first-stage selection model. In line with our predictions, a focal influencer is significantly more likely to be selected by a brand when a similar influencer is also selected (b = 1.646, $z$ = 89.85, $p$ < .001). Selection probabilities are also significantly greater for female influencers (b = .069, $z$ = 6.78, $p$ < .001) and those with larger follower sizes (b = .011, $z$ = 14.87, $p$ < .001). Higher influencer activity (b < .001, $z$ = 1.02, $p$ = .309) and the increasing trend in their activity (b = .030, $z$ = 1.25, $p$ = .212), though not significant, are associated with larger selection probabilities. The inverse Mills ratio (IMR), representing unobserved aspects of influencer selection determined by brands and influencers (e.g., prior relationship between them), is included as an independent variable in all second-stage models, alleviating the concern that the estimated effect of influencer marketing spend on engagement is prone to selection bias.

[Insert Table 4 about here]

***Engagement Model***

[5] To obtain the time trend, we regress an influencer's posting activity on each day against the days in chronological order ($t$ = 1, 2, …, 90).

To estimate the effect of influencer marketing spend on engagement, we used a log-log specification for the second-stage model, which facilitates the interpretation of the coefficients for (log) influencer marketing spend as engagement elasticity, which is a unit-free and generalizable measurement. By identifying factors that moderate this elasticity, we also seek to understand what enhances (or weakens) the effectiveness of influencer marketing spend. To that end, we estimate the following second-stage engagement model:

$$
\begin{aligned}
\ln(Engagement_{ij}) &= \beta_0 + \beta_1 \ln(IMS_{ij}) + \beta_2 Influencer\ Activity_{ij} + \beta_3 Influencer\ Originality_{ij} \\
&+ \beta_4 Follower\ Size_{ij} + \beta_5 Follower\ Brand\ Fit_{ij} + \beta_6 Post\ Positivity_{ij} \\
&+ \beta_7 Sponsor\ Salience_{ij} + \beta_8 New\ Product\ Launch_{ij} \\
&+ \beta_9 Influencer\ Activity_{ij} \times \ln(IMS_{ij}) + \beta_{10} Influencer\ Originality_{ij} \times \ln(IMS_{ij}) \\
&+ \beta_{11} Follower\ Size_{ij} \times \ln(IMS_{ij}) + \beta_{12} Follower\ Brand\ Fit_{ij} \times \ln(IMS_{ij}) \\
&+ \beta_{13} Post\ Positivity_{ij} \times \ln(IMS_{ij}) + \beta_{14} Sponsor\ Salience_{ij} \times \ln(IMS_{ij}) \\
&+ \beta_{15} New\ Product\ Launch_{ij} \times \ln(IMS_{ij}) + \boldsymbol{C}_{ij}\boldsymbol{\alpha} + \varepsilon_{ij}, \quad (2)
\end{aligned}
$$

where $i$ and $j$ denote post $i$ and influencer $j$; $\ln(Engagement_{ij})$ and $\ln(IMS_{ij})$ are the natural logarithms of engagement (i.e., number of reposts) and of influencer marketing spend, respectively;[6] and the seven moderating variables are as defined in the hypothesized conceptual model. Note that the interaction terms involve variables that are not mean-centered. Furthermore, $\boldsymbol{C}_{ij}$ is vector of control variables, including promotion, post length, post number in campaign, brand types (service vs. product brand, premium vs. value brand, foreign vs. local brand), brand categories (29 categories), influencer gender, Golden Week, weekend, and the IMR from the first-stage model. Finally, $\beta_0$, $\beta_1$,…, $\beta_{15}$, and $\boldsymbol{\alpha}$ are (scalar or vector) coefficients, and $\varepsilon_{ij}$ denotes an independent error term.

[6] We added .01 to the number of reposts before taking the logarithm, to include posts that were not reposted.

We started the analysis with lower-order terms (i.e., influencer marketing spend, seven moderators, and controls) (Model 1). The results in Table 5 indicate substantive, significant engagement elasticity; *ceteris paribus*, a 1% increase in influencer marketing spend increases engagement by .457% ($t = 16.96$, $p < .001$). Therefore, increasing the influencer marketing budget can increase engagement. Note that the variance inflation factors in Model 1 (no interaction terms) are all below 2.0, alleviating collinearity concerns.

We then included the interaction terms, as specified in the engagement model in Equation 2 (Model 2), to test $H_2$, $H_3$, $H_6$, and $H_7$. We find that influencer originality significantly enhances engagement elasticity (b = .592, $t = 5.18$, $p < .001$), such that engagement is more responsive to greater influencer marketing spend when the influencer posts more original content, in support of $H_2$. Also, as hypothesized in $H_3$, engagement elasticity increases significantly with larger follower size (b = .019, $t = 5.92$, $p < .001$). We find that engagement elasticity increases when the sponsor brand is more salient in the post (b = .092, $t = 3.33$, $p < .001$), in support of $H_{6a}$. This finding suggests that instead of prompting ad avoidance, sponsor salience likely enhances content value by making the post more informative. Finally, engagement elasticity diminishes in response to posts about new product launches (b = -.488, $t = -6.96$, $p < .001$), consistent with $H_{7b}$. The result suggests that the risks surrounding new product launches likely prohibit consumers' responsiveness and weaken engagement elasticity. The coefficients of the IMR are insignificant in Models 1 and 2; unobserved aspects of influencer selection, such as prior relationships between influencers and brands, thus appear unlikely to affect engagement. For completeness, we introduce the interactions separately and provide these model estimation results in Web Appendix B (Models 2a–2c). Since the trend in influencer activity (i.e., one of the variables used in the exclusion restriction) is insignificant in the selection model, we alternatively estimated the engagement model by excluding this variable from the selection model (see Web Appendix C). Furthermore, Web Appendix D contains the estimation results without the IMR. All the estimates remain similar in sign, relative magnitude, and significance.

As a robustness check, we used another engagement metric—*number of comments* an influencer marketing post generates within 24 hours of posting—as the dependent variable. The results for $H_2$, $H_3$, $H_6$, and $H_7$ remain consistent and robust, offering further confidence in the findings derived from our engagement model (Web Appendix E).

[Insert Table 5 about here]

### *Delineating the Nonlinear Moderating Effects*

To test $H_1$, $H_4$, and $H_5$, we consider the inverted U-shaped moderating effects of three moderators—influencer activity, follower–brand fit, and post positivity—on engagement elasticity. Specifically, we add interactions of the quadratic forms of the proposed moderators with $\ln(IMS_{ij})$ (i.e., $Influencer\ Activity_{ij}^2 \times \ln(IMS_{ij})$, $Follower\ Brand\ Fit_{ij}^2 \times \ln(IMS_{ij})$, and $Post\ Positivity_{ij}^2 \times \ln(IMS_{ij})$) and the simple quadratic forms of the three moderators (i.e., $Influencer\ Activity_{ij}^2$, $Follower\ Brand\ Fit_{ij}^2$, and $Post\ Positivity_{ij}^2$) to the engagement model in Equation 2 to test for curvilinear moderating effects (Jaccard and Turrisi 2003; Lind and Mehlum 2010; Wielgos, Homburg, and Kuehnl 2021). We introduced the interactions of each quadratic moderator with $\ln(IMS_{ij})$ stepwise (Models 3a–3c), then collectively (Model 3).

As Table 5 reveals, the squared interaction term between influencer activity and $\ln(IMS_i)$ is negative and significant (Model 3a: b = -.001, $t$ = -4.19, $p$ < .001; Model 3: b = -.001, $t$ = -4.21, $p$ < .001), indicating that engagement elasticity varies across different levels of influencer activity in an inverted U-shaped manner, in support of $H_1$. Similarly, the results reveal significant inverted U-shaped moderating effects for follower–brand fit (Model 3b: b = -8.185, $t$ = -3.09, $p$

< .01; Model 3: b = -7.825, $t$ = -3.00, $p$ < .01) and post positivity (Model 3c: b = -.250, $t$ = -2.32, $p$ < .05; Model 3: b = -.250, $t$ = -2.35, $p$ < .05), in support of $H_4$ and $H_5$, respectively.[7] The moderating effects of influencer originality, follower size, sponsor salience, and new product launch remain robust to these alternative model specifications (Models 3a–3c, and Model 3), such that we obtain strong evidence for the validity of $H_2$, $H_3$, $H_6$, and $H_7$.

To probe these results further, we sought to predict engagement elasticity conditional on the values of influencer activity, follower–brand fit, and post positivity (Model 3; all other variables remained at their mean) and plotted the predicted values. Figure 2 illustrates the hypothesized inverted U-shaped moderating effects. As Panel A shows, engagement elasticity increases when influencer activity rises to an optimal level, then diminishes beyond that turning point ($TP_{\text{influencer activity}}$ = 64.781). We note a significant positive slope at the low end of influencer activity (b = .020, $t$ = 6.71, $p$ < .001) and a negative slope at the high end (b = -.038, $t$ = -3.36, $p$ < .001).[8] Similar inverted U-shaped patterns appear in Panels B and C of Figure 2, revealing that follower–brand fit and post positivity strengthen engagement elasticity initially (follower–brand fit: $b_{\text{left}}$ = 1.358, $t$ = 2.11, $p$ < .05; post positivity: $b_{\text{left}}$ = .466, $t$ = 2.02, $p$ < .05), then weaken it when they reach high levels (follower–brand fit: $b_{\text{right}}$ = -6.439, $t$ = -3.17, $p$ = <.001; post positivity: $b_{\text{right}}$ = -.457, $t$ = -2.61, $p$ < .01). The turning points are located well within the respective data ranges ($TP_{\text{follower–brand fit}}$ = .087; $TP_{\text{post positivity}}$ = .033). These results provide further evidence in support of $H_1$, $H_4$, and $H_5$.

[Insert Figure 2 about here]

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[7] We experimented with specifications that also included cubic interactions of the three moderators with $\ln(IMS_{ij})$; their insignificant coefficients indicate support for inverted U-shaped moderating effects.
[8] We calculated the slopes at low and high values of the moderators, as well as their turning points, using unstandardized regression coefficients (Jaccard and Turrisi 2003; Wielgos, Homburg, and Kuehnl 2021).

To confirm the robustness of our findings, we employed another approach to investigate the nonlinear moderating effects. Specifically, for each proposed moderator, we divided posts with a median split, then estimated Equation 2 separately for the two subsamples. If inverted U-shaped relationships exist between the moderators and engagement elasticity, we should observe initially strong elasticity (low levels of the moderators) that diminishes as the moderators increase (high levels of the moderators). Web Appendix F presents the estimation results. Consistent with $H_1$, engagement elasticity strengthens at first (b = .091, $t = 7.08$, $p < .001$) but later weakens (b = -.003, $t = -1.58$, $p = .114$) with growing influencer activity (Columns 1 and 2, Web Appendix F). Higher follower–brand fit also first increases (b = 3.752, $t = 2.08$, $p < .05$) and then reduces (b = -1.961, $t = -4.19$, $p < .001$) engagement elasticity, in support of $H_4$ (Columns 3 and 4, Web Appendix F). In a similar nonlinear pattern, a higher level of post positivity strengthens elasticity initially (b = .206, $t = 1.82$, $p = .069$), then weakens it (b = -.191, $t = -1.10$, $p = .272$), in line with $H_5$ (Columns 5 and 6, Web Appendix F). This median-split approach provides managerial insights related to the two subsamples: Brands can use their industry medians as a benchmark, then decide whether to increase or decrease the levels of the moderators to achieve more effective influencer marketing campaigns.

***Additional Robustness Check***

We already have replicated our main model results with an alternative dependent variable (i.e., number of comments) and validated the nonlinear moderating effects with different approaches to ensure the robustness of our findings. In this section, we present several additional robustness checks to provide further evidence of the validity of the proposed effects. Column 1 of Web Appendix G lists the results when we take the natural logarithm of follower size, to account for its skewness. In Column 2, we present the Model 3 (full model) results when we control for the fixed effects of days (i.e., every date of October), to alleviate concerns of seasonality in consumer engagement. Column 3 depicts the results when we operationalize sponsor salience with only the count of URLs linked to the sponsor brand's website or online shop. In all columns, the estimation results for $H_1$–$H_7$ are consistent with those obtained from our initial Model 3, suggesting the proposed effects are robust to the alternative model specifications.

With regard to the moderating role of post positivity, we complement our initial deductive, top-down dictionary-based approach with abductive, bottom-up approaches to offer convergent insights (Humphreys and Wang 2018). Specifically, we used two proven, reliable algorithms for text classification: a naïve Bayesian classifier and a support vector machine classifier (Tirunillai and Tellis 2012). Then we reestimated Model 3 using the post positivity yielded by the two algorithms. The estimation results are consistent with $H_5$; as we specify in Web Appendix H, the squared interaction term between post positivity and $\ln(IMS_{ij})$ is significantly negative for both algorithms (naïve Bayesian classifier: b = -1.998, $t$ = -2.31, $p$ < .05; support vector machine classifier: b = -1.358, $t$ = -3.14, $p$ < .01; Columns 1 and 2 of Table WH1). Figure WH1 graphically depicts the inverted U-shaped moderating effects of post positivity, yielded by these two algorithms, on engagement elasticity, providing visual evidence in support of $H_5$.

Finally, we check the level of analysis. Both the dependent variable (i.e., number of reposts) and the focal independent variable (i.e., influencer marketing spend) are at the influencer marketing post level, so single posts provide the fundamental unit of analysis. Our empirical analyses based on each post identify the impact of post-level heterogeneity on engagement elasticity. But our data also contain information at the influencer level, such that we can nest the individual posts within different influencers. To test the validity of our hypotheses, we therefore implement a mixed-effects model that controls for potential heterogeneity among influencers, using the following alternative specification:

$$\ln(Engagement_{ij}) = b_{0j} + b_{1j}\ln(IMS_{ij}) + b_{2j}Influencer\ Activity_{ij} + b_{3j}Influencer\ Originality_{ij}$$
$$+b_{4j}Follower\ Size_{ij} + b_{5j}Follower\ Brand\ Fit_{ij} + \ b_{6j}Post\ Positivity_{ij}$$
$$+b_{7j}Sponsor\ Salience_{ij} + b_{8j}New\ Product\ Launch_{ij}$$
$$+b_{9j}Influencer\ Activity_{ij}^2 + b_{10j}Follower\ Brand\ Fit_{ij}^2 + \ b_{11j}Post\ Positivity_{ij}^2$$
$$+b_{12j}Influencer\ Activity_{ij} \times \ln(IMS_{ij}) + b_{13j}Influencer\ Activity_{ij}^2 \times \ln(IMS_{ij})$$
$$+b_{14j}Influencer\ Originality_{ij} \times \ln\left(IMS_{ij}\right) + b_{15j}Follower\ Size_{ij} \times \ln(IMS_{ij})$$
$$+b_{16j}Follower\ Brand\ Fit_{ij} \times \ln(IMS_{i}) + \ b_{17j}Follower\ Brand\ Fit_{ij}^2 \times \ln(IMS_{ij})$$
$$+b_{18j}Post\ Positivity_{ij} \times \ln(IMS_{ij}) + \ b_{19j}Post\ Positivity_{ij}^2 \times \ln(IMS_{ij})$$
$$+b_{20j}Sponsor\ Salience_{ij} \times \ln(IMS_{ij}) + b_{21j}New\ Product\ Launch_{ij} \times \ln(IMS_{ij}) + \boldsymbol{C}_{ij}\boldsymbol{d} + \epsilon_{ij}, \quad (3)$$

where $i$ and $j$ denote post $i$ and influencer $j$; most of the variables are as previously defined; $b_{0j}$ is the random intercept; and $b_{1j}, b_{2j}, \dots, b_{21j}$ are random slopes. We denote $\boldsymbol{b}_j = (b_{0j}, b_{1j}, b_{2j}, \dots, b_{21j})'$, such that $\boldsymbol{b}_j$ is multivariate normally distributed $\boldsymbol{b}_j \sim MVN(\boldsymbol{\mu}, \boldsymbol{G})$. We also assume the random effects are independent;[9] the off-diagonal elements of the variance covariance matrix $\boldsymbol{G}$ are 0. Finally, $\boldsymbol{d}$ is a vector of fixed coefficients, and $\epsilon_{ij}$ is an independent error. We first include the random intercept (Column 1, Web Appendix I), and then all the random effects specified in Equation 3 (Column 2, Web Appendix I). The results are comparable to those in Model 3 in Table 5, revealing consistent estimates across the three models in their signs, relative magnitude, and significance. Thus, the results appear robust to alternative specifications that account for influencer-level mixed effects.

[9] Estimating the dependence between influencer-level random effects is theoretically feasible but computationally intractable with our empirical data, which contain many random effects (i.e., 2,412 influencers).

***Post Hoc Analyses for Managerial Insights***

An advantage of estimating the engagement model is that we can derive practical insights into how firms can better allocate their influencer marketing budget across influencers and help firms understand how much upward potential they have. We take the perspective of firms that incentivize influencers to maximize profits, through engaging the followers. Assuming a constant engagement elasticity (i.e., for a given influencer the elasticity is the same across the range of influencer marketing spend, in line with the log-log model that was used) for each influencer, the key decision is how to allocate influencer marketing budget across influencers, regardless of the number of posts the allocated amount translates into. We focus on the budget allocation decision, rather than on determining the size of the budget. Specifically, given firms' existing influencer marketing budget, we compare how firms should allocate their budget across influencers optimally versus how they actually have allocated their budget.

We leverage the optimal allocation rule recommended by Peers, van Heerde, and Dekimpe (2017). Assuming equal per-engagement profit contribution for all influencers, the optimal budget allocation is proportional to the (product of) engagement elasticity and the base engagement levels of the influencers. The intuition is that more budget should be allocated to those with stronger responsiveness to sponsorship and larger size of base engagement. Consider an example from our data set: A hair styling brand spent $264 on influencer marketing, including $234 (89%) for posts by Influencer A and $30 (11%) for posts by Influencer B. Their engagement elasticities are .16 and .57, while their base engagement levels are 19 and 15 reposts, respectively. This means that the budget allocation weights should have been 3.04 (i.e., $.16 \times 19$) for Influencer A and 8.55 (i.e., $.57 \times 15$) for Influencer B, or 26.2% (i.e., $\frac{.16\times19}{.16\times19+.57\times15}$) for Influencer A and 73.8% (i.e., $\frac{.57\times15}{.16\times19+.57\times15}$) for Influencer B. If this firm had adopted this optimal budget allocation, it could have increased consumer engagement by 42.0% relative to that achieved with its actual allocation, corresponding to 163 more reposts (from 389 to 552 reposts). When we perform similar calculations for all the firms in our data set, to determine the difference in engagement achieved with optimal versus actual budget allocations, we find that on average, the firms could achieve a 16.6% increase in engagement.[10] This finding suggests that the firms in our data set are sub-optimally allocating their budget across influencers, and there is considerable upward potential in generating engagement if they were to account for influencers' engagement elasticities (and base engagement levels) in their decisions.

In another set of auxiliary analyses, we varied each of the moderating factors and examined their impacts on influencer marketing effectiveness (i.e., engagement elasticity), while keeping all other variables at their mean levels (see Web Appendix J). The results offer clearer insights into the managerially relevant magnitude of these moderating effects. They also highlight some unique tensions for marketers who design influencer marketing campaigns. When selecting on the basis of influencer activity, follower–brand fit, and post positivity, more is not always better. For example, a sponsored post shared by a highly active influencer, one with very high levels of follower–brand fit, and one showing very high post positivity (2 SD beyond the optimal points) would lose 21.0%, 31.4%, and 22.4% in engagement elasticity, respectively.

## General Discussion

This research sheds new light on the factors that alter influencer marketing effectiveness. By accounting for influencer marketing spend, we assess the efficacy of leveraging influencers to

[10] Influencers' engagement elasticities and base engagement levels were obtained through estimating Equation 3 (mixed-effects model) with all independent variables mean-centered. Alternatively, we measured influencers' base engagement levels with the average number of reposts across their posts and the optimal allocation results are similar, with a 16.7% increase in engagement. Budget allocations across influencers require the existence of more than one influencer, so this analysis refers only to firms that contract with more than one influencer.

encourage consumer engagement. Factors related to the influencers, their followers, and their sponsored posts all have critical roles in determining the level of influencer marketing effectiveness. In outlining these nuanced effects, we reveal the importance of communication factors for decisions about influencer marketing campaigns.

### *Theoretical Contributions*

This research enriches existing marketing literature by integrating firms' spending on influencer marketing as a measure of influencer marketing effectiveness. Prior studies of influencer marketing mostly document the impacts of source and post characteristics on various key outcomes (see Table 1), but we lack critical assessments of the costs required by the campaigns. Because influencer spend varies substantially, ignoring such costs limits the accuracy of the findings regarding the effectiveness of influencer marketing to engage consumers (Batra and Keller 2016). We extend efforts to integrate media spending in determinations of advertising elasticities (Dinner, Van Heerde, and Neslin 2014; Sethuraman, Tellis, and Briesch 2011) to the domain of influencer marketing. As research into influencer marketing grows, it is critical to investigate the extent of its effectiveness by using data about both cost and engagement outcomes, because achieving higher engagement returns remains a key concern for marketers.

Drawing on communication theory (Lasswell 1948; Shannon and Weaver 1949), this study delineates how diverse factors pertaining to the influencer (sender), followers (receiver), and posts (message) can influence influencer marketing effectiveness. In relation to sender characteristics, we identify three easily observable characteristics (influencer activity, originality, and follower size). Influencer activity exerts an inverted U-shaped effect; excessive activity appears to lead to information overload. This finding thus helps reconcile mixed results in prior studies pertaining to the effects of posting activity (Stephen et al. 2017; Suh et al. 2010).

Moreover, unlike celebrity endorsers, influencers can create content for brands, and the extent to which they share self-created (vs. other-created) content offers a unique characteristic for consideration. We find that influencers who post more original content are more effective senders, because they increase engagement elasticity. In line with seeding strategy research, which generally suggests the superiority of seeding well-connected members of a network (Hinz et al. 2011; Libai, Muller, and Peres 2013), we find that follower size enhances effectiveness.

Characteristics of followers also define a campaign's effectiveness. Extant endorsement literature often cites a positive impact of brand fit (Bergkvist and Zhou 2016), but as we find, follower–brand fit can have an inverted U-shaped effect on influencer marketing effectiveness. This result echoes findings in behavioral targeting literature (Boerman, Kruikemeier, and Borgesius 2017) that suggests both the benefits and downsides of precise targeting approaches. But as long as follower–brand fit is not too high, influencer marketing can deliver surprises to followers, which is an important goal of marketers, considering the mounting advertising clutter.

Finally, our investigation of post characteristics demonstrates some of the unique features of influencer marketing. Previous literature suggests that more positive content is more viral (Berger and Milkman 2012), but we find that a blend of positive and negative content can yield the greatest effectiveness. In most cases, consumers realize that influencers are paid to advocate for a brand or product, so they may start to question the influencers' authenticity if they share only positive comments about an endorsed brand (McQuarrie, Miller, and Phillips 2013). Moreover, previous literature offers conflicting views regarding the impact of sponsor salience on advertising effectiveness. Our results support the view that including more links to the sponsor brand can enhance a post's informativeness (Lou and Yuan 2019), confirming that sponsor salience enhances influencer marketing effectiveness. Last but not least, while competing arguments exist regarding whether new product launches motivate or inhibit consumers' tendency to engage with influencer marketing efforts, our results confirm the latter view in that consumers are less responsive to posts about new product launches likely due to heightened risks and social desirability concerns.

***Managerial Implications***

Influencer marketing allows firms to crowdsource the resources that influencers possess, including their follower networks, creative content, personal positioning, and follower trust, to enhance marketing communications (Leung, Gu, and Palmatier 2022). However, the costs of these campaigns vary widely. Without cost considerations, firms cannot accurately evaluate the effectiveness of their influencer marketing efforts. In establishing a positive effect of influencer marketing spend on consumer engagement, our findings confirm the effectiveness of this communication practice. The estimation of engagement elasticity also sheds light on how firms actually allocate their budgets across influencers, relative to how they should do so. As our post hoc analysis indicates, the average firms in our data set are allocating their budgets suboptimally and have substantive upward potential with regard to generating engagement.

Our findings also offer insights for managing influencer marketing, in terms of influencer selection, follower considerations, and content briefings. In addition to investing in influencers with more followers, firms can enhance elasticity by selecting influencers who transmit more original content. Furthermore, they should encourage influencers to make the sponsor brand more salient in the posts, by incorporating clickable brand mentions and URL links. However, by accounting for influencer marketing spend, our findings may appear to contradict some managerial intuitions. For example, posts introducing new products may be shared more, because they contain novel and interesting content (Tellis et al. 2019), but firms also should be aware that the engagement elasticity they evoke is lower than that of posts that remind consumers of existing products, likely due to the heightened risks associated with new product launches. Yet the firms in our data set spent significantly more on influencer marketing posts that promote new products. Existing products receive relatively less attention and resources, even though such allocations would be more effective—consistent with the notion that spending on less favored situations is beneficial (Van Heerde et al. 2013).

Firms also must attend to three key tensions related to influencer activity, follower–brand fit, and post positivity. Efforts to move these decision factors toward their optimal levels can greatly enhance the effectiveness of influencer marketing spend. Specifically, influencers who engage in a medium level of posting activity are preferable; in Figure 2, Panel A, we find that average firms in our data set could increase the effectiveness of their influencer marketing efforts by 53.8% if they selected influencers who engaged in more posting activity, up to the optimal level. However, followers with a very high degree of shared interest with the brand may not be the best group to target. The average firms in our data set already were targeting follower groups at nearly optimal levels of follower–brand fit (Figure 2, Panel B). Finally, firms should encourage influencers to include some critical content in their posts to enhance the perceived credibility of the messages. Figure 2, Panel C, indicates that the average firms in our data set overshoot in terms of post positivity; they could increase their influencer marketing effectiveness by 1.9% by instructing influencers to offer some slightly negative content in their posts.

***Further Research and Limitations***

Our study is subject to several limitations that also suggest future research directions. First, we focus on influencer activity, originality, and follower size as important drivers of influencer marketing effectiveness. Research that assesses other influencer characteristics, such as consistency (based on historical posts), personality (e.g., humorous, confident), perceived uniqueness, authenticity, and endorsement history, could help firms gain more insights into the determinants of effectiveness. Similarly, we measure follower–brand fit as an important follower characteristic; additional research could look into followers' homogeneity (e.g., demographics, interests) or influencer–follower relationship strength to glean more insights along these lines.

Second, our empirical context is Weibo, a microblogging platform similar to Twitter. In operationalizing post characteristics, such as positivity and sponsor salience, we rely on text analyses. The increasingly diverse platforms and tools available for influencer marketing may require different content measures though. For example, Instagram supports visually engaging images; YouTube allows influencers to create videos with in-depth information that can remain accessible for a long time. Contents from short video sharing apps (e.g., TikTok) provide a more short-lived but entertaining function. Further research might move beyond text-based analyses to address content factors such as aesthetics or the entertainment value of visual content. In addition, our results reveal that posts about new product launches reduce influencer marketing effectiveness, possibly due to the heightened risks associated with new products. From another view, because firms tend to overinvest in advertising to promote new products (Krishnan and Jain 2006), repetition and wear-out may occur (Bruce, Foutz, and Kolsarici 2012), which diminishes consumers' responsiveness to specific influencer marketing efforts. While we do not have data to evaluate whether influencer marketing effectiveness decreases with higher non-influencer marketing spend, future research could investigate such potential negative synergy.

Third, classic models of communication (Lasswell 1948) often include details about who (sender) says what (message) in which channel (medium) and to whom (receiver). We identify the effects of sender, receiver, and message characteristics, but our data are limited to a single social media platform (medium), which may have its own unique restrictions. For example, our findings reveal that selecting influencers who create original posts enhances engagement elasticity, but it has a negative main effect on consumers' reposting. This result may be specific to Weibo, considering the relatively high levels of content moderation and control it imposes and the associated risks of reposting for consumers. Additional research could test our conceptual framework in another medium. Then a related research direction might address specific channel or medium characteristics and their impacts on influencer marketing effectiveness. As Shannon and Weaver (1949) suggest, noise in the communication process might interfere with the channel or distort the message; noise such as clutter due to competitive influencer posts and claims might affect influencers' communication with followers. In addition, our data set consists of influencer marketing posts gathered over one month; data spanning a longer period, involving more influencers (especially smaller ones), could help generalize the insights from the current study.

Fourth, even if generating consumer engagement (e.g., likes, comments, reposts) is a primary objective of influencer marketing campaigns, not every form of engagement is created equal. Consumers may exhibit varied search behavior or purchase conversion likelihoods when they engage with different influencers or posts. With currently available technologies, firms can track click-throughs and website traffic (Lee, Hosanagar, and Nair 2018), then measure which sales result from particular influencer marketing posts. Further research should examine the drivers of click-through– or sales-based elasticity outcomes to determine how specific influencer marketing strategies might exert direct impacts on firms' bottom lines.

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# TABLE 1
# REVIEW OF INFLUENCER MARKETING LITERATURE

| Authors | Research Context | Accounts for Costs | Influencer Factors | Follower Factors | Post Factors | Other Factors | Outcomes | Theory | Key Findings |
|---|---|---|---|---|---|---|---|---|---|
| Bharadwaj et al. (2022) | Videos of live sales presentations | No | Not studied | Not studied | Face presence[A]; emotional displays[A] | Product price[MO]; promotion[MO] | Sales | Emotions as social information model | Emotional displays in livestream retailing have negative U-shaped effects on sales over time. |
| Breves et al. (2019) | Experiment and survey about Instagram influencers | No | Influencer-brand fit[A] | Not studied | Not studied | Parasocial relationships[MO] | Perceived credibility; brand evaluation; behavioral intentions | Social adaptation; attribution theory | Influencer–brand fit positively affects influencer credibility and ad outcomes, especially for followers with weak parasocial relationships. |
| De Veirman, Cauberghe, and Hudders (2017) | Experiments about Instagram influencers | No | Follower size[A]; perceived popularity[ME]; opinion leadership[ME]; number of followees[MO] | Not studied | Not studied | Product divergence[MO] | Influencer likeability | Heuristic processing; naïve theories | Influencers with more followers are perceived as more popular and likable; the effects depend on number of followees and product divergence. |
| De Veirman and Hudders (2020) | Experiment about Instagram influencers | No | Source credibility[ME] | Not studied | Sponsorship disclosure[A]; ad recognition[ME]; message sidedness[MO] | Skepticism[ME] | Brand attitude | Persuasion knowledge model; reactance theory | Sponsorship disclosure negatively affects brand attitude through enhanced ad recognition and skepticism, which lowers influencer credibility, especially when using a one-sided message. |
| Gong et al. (2017) | Field experiment with a media company and influencers on Weibo | Yes[1] | Follower size[MO]; daily number of tweets[MO] | Not studied | Tweet vs. tweet and retweet[A] | Number of company followers[ME] | Show viewing | - | Influencer retweets increase viewing if the show tweet is informative; they are more effective than company tweets in bringing new followers, which indirectly increases viewing. |
| Hughes, Swaminathan, and Brooks (2019) | Sponsored influencer posts from Motherhood | Yes[2] | Influencer expertise[A] | Not studied | Hedonic value[A] | Campaign incentive[A]; campaign intent [MO]; platform type[MO] | Engagement | Elaboration likelihood model | Effects of sponsored blogging on engagement depend on influencer characteristics and post content, which are further moderated by platform type and campaign intent. |
| Lanz et al. (2019) | Music creators from a leading music platform | No | Status difference[A] | Not studied | Not studied | Not studied | Follow-backs | Seeding strategies; social identity theory | Responsiveness of seeding targets declines with status difference; unknown music creators benefit from targeting low-status users rather than influencers. |
| Lee and De Fortuny (2021) | Online survey with social media users | No | Influencer typicality[A] | Not studied | Not studied | Perceived homogeneity of brand consumers[ME] | Strength of brand reference group associations | Stereotype change | Influencer typicality shapes perceived homogeneity of brand consumers, which affects the strength and tightness of brand associations. |
| Lee and Eastin (2020) | Experiment about Instagram influencers | No | Perceived sincerity[A] | Not studied | Not studied | Consumer envy[MO]; product type[MO] | Attitude toward influencer; brand attitude; purchase intention | Brand personality; schema theory | Influencer sincerity positively affects consumer attitudes; the effects are contingent on consumer envy and product types. |
| Lou and Yuan (2019) | Online survey with social media users | No | Trustworthiness[A]; attractiveness[A]; similarity to followers[A] | Not studied | Informative value[A] | - | Perceived trust; brand awareness; purchase intentions | Source credibility; advertising content value | Informative value of influencer content, influencer trustworthiness, attractiveness, and similarity to the followers positively affect follower trust, which influence brand awareness and purchase intentions. |
| Pei and Mayzlin (2021) | Bayesian persuasion model | Yes[3] | Not studied | Prior belief[MO] | Affiliation[A] | Cost of information acquisition[MO]; disclosure regime[MO] | Value of information | Persuasion theory | Affiliation decision depends on the cost of information acquisition, consumers' prior belief, and disclosure regime. |
| Valsesia, Proserpio, and Nunes (2020) | Twitter posts; lab experiments about influencers | No | Follower size[MO]; number of followees[A]; perceived autonomy[ME]; perceived influence[ME] | Not studied | Not studied | - | Engagement | Heuristic processing | Following fewer others conveys greater autonomy, which positively affects perceived influence and engagement. |
| Yuan and Lou (2020) | Online survey with social media users | No | Perceived credibility[A]; perceived fairness[A] | Not studied | Not studied | Parasocial relationship[ME] | Product interest | Source credibility; communication justice | Influencer credibility and fairness positively affect the strength of parasocial relationship with influencers, which increases followers' interests in influencer-promoted products. |
| This paper | Sponsored influencer posts on Weibo | Yes (influencer marketing spend[A]) | Influencer activity[MO]; influencer originality[MO]; follower size[MO] | Follower-brand fit[MO] | Post positivity[MO]; sponsor salience[MO]; new product launch[MO] | - | Engagement | Communication model | Factors related to influencers, their followers, and their sponsored posts have critical roles in determining influencer marketing effectiveness in terms of engagement elasticity. |

Notes: [A] = antecedent; [ME] = mediator; [MO] = moderator.

[1] Each influencer was paid 1,000 CNY for their participation in a field experiment. The authors computed the returns on tweeting across experimental conditions.

[2] The cost for each blogger campaign was considered in a post hoc analysis. The authors calculated return on engagement (RoE) by dividing the total revenue generated by the total cost for each blogger campaign; they find significant positive effects of blogger expertise and campaign incentives on RoE.

[3] In the model setup, the firm may manipulate the review process by offering the influencer payment in exchange for affiliation.

## TABLE 2
## VARIABLE OPERATIONALIZATIONS

| Variable | Definition | Operationalization | References |
|---|---|---|---|
| **Dependent Variable** | | | |
| Engagement | Number of reposts generated on an influencer marketing post | Number of reposts an influencer marketing post generated within 24 hours of posting | Valsesia, Proserpio, and Nunes (2020) |
| **Independent Variable** | | | |
| Influencer marketing spend | Cost of an influencer marketing post | Amount of money (in dollars) spent on an influencer marketing post | - |
| **Sender (Influencer) Characteristics** | | | |
| Influencer activity | Frequency with which an online influencer transmits content on social media | Total number of posts (both sponsored and non-sponsored) an online influencer published on Weibo in the previous 90 days, prior to the campaign | Gong et al. (2017); Stephen et al. (2017) |
| Influencer originality | Degree to which an online influencer creates original content | Ratio of number of original posts (both sponsored and non-sponsored) to total number of posts published in the past 90 days, prior to the campaign | - |
| Follower size | Number of followers an online influencer has on a social media platform | Total number of followers an online influencer has on Weibo (in millions), prior to the campaign | Hughes, Swaminathan, and Brooks (2019) |
| **Receiver (Follower) Characteristics** | | | |
| Follower–brand fit | Degree to which the interests of an online influencer's followers match with the associated domains of the sponsor brand of an influencer marketing post | Percentage of an online influencer's followers whose interests matches with the associated domains of the sponsor brand of an influencer marketing post | - |
| **Message (Post) Characteristics** | | | |
| Post positivity | Degree to which the content of an influencer marketing post is positive | Ratio of the difference between positive and negative words to the total number of emotional words in an influencer marketing post [(number of positive words – number of negative words) / (number of positive words + number of negative words + 1)] | Berger and Milkman (2012) |
| Sponsor salience | Degree to which the sponsor brand is prominent in an influencer marketing post | Total count of @s (linked to the sponsor brand's own Weibo account) and URLs (linked to the sponsor brand's website or online shop) in an influencer marketing post | Soboleva et al. (2017) |
| New product launch | Whether an influencer marketing post is related to new product launch | Binary variable equal to 1 if an influencer marketing post is related to new product launch | - |
| **Control Variables** | | | |
| Promotion | Whether an influencer marketing post is related to promotions | Binary variable equal to 1 if an influencer marketing post is related to promotions | - |
| Post length | Length of an influencer marketing post | Total number of characters in an influencer marketing post | Berger and Milkman (2012) |
| Post number in campaign | Number of influencer marketing posts within the same campaign | Total number of influencer marketing posts within the same campaign as the focal influencer marketing post | - |
| Service (vs. product) brand | Whether the sponsor brand of an influencer marketing post is a service or product brand | Binary variable equal to 1 if the sponsor brand of an influencer marketing post is a service (vs. product) brand | Lovett, Peres, and Shachar (2013) |
| Premium (vs. value) brand | Whether the sponsor brand of an influencer marketing post is a premium or value brand | Binary variable equal to 1 if the sponsor brand of an influencer marketing post is a premium (vs. value) brand | Lovett, Peres, and Shachar (2013) |
| Foreign (vs. local) brand | Whether the sponsor brand of an influencer marketing post is a foreign or local brand | Binary variable equal to 1 if the sponsor brand of an influencer marketing post is a foreign (vs. local Chinese) brand | - |
| Brand category | The category of the sponsor brand of an influencer marketing post | Binary variable equal to 1 if the sponsor brand of an influencer marketing post belongs to a particular category (e.g., beauty products, e-commerce platforms, electronics) | - |
| Influencer gender | Gender of the online influencer | Binary variable equal to 1 if the online influencer is female (vs. male) | Hughes, Swaminathan, and Brooks (2019) |
| Golden week | Whether an influencer marketing post is initiated during the Chinese Golden Week holiday in October | Binary variable equal to 1 if an influencer marketing post is initiated during the Chinese Golden Week holiday | Ishihara and Ching (2019) |
| Weekend | Whether an influencer marketing post is initiated on weekends | Binary variable equal to 1 if an influencer marketing post is initiated on weekends | Hughes, Swaminathan, and Brooks (2019) |

# TABLE 3
# DESCRIPTIVE STATISTICS AND CORRELATIONS

| Variables | Mean | Median | SD | Min | Max | Correlation Matrix | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| 1. Engagement | 1037.78 | 201.00 | 21060.69 | .00 | 1582398.00 | 1.00 | | | | | | | | | | | | | | | | | |
| 2. Influencer marketing spend (in dollars) | 1002.97 | 292.86 | 2622.79 | .43 | 92857.14 | .33*** | 1.00 | | | | | | | | | | | | | | | | |
| 3. Influencer activity | 13.37 | 4.93 | 19.90 | .00 | 187.67 | -.02. | -.12*** | 1.00 | | | | | | | | | | | | | | | |
| 4. Influencer originality | .61 | .65 | .21 | .03 | 1.00 | -.01 | -.09*** | .33*** | 1.00 | | | | | | | | | | | | | | |
| 5. Follower size (in millions) | 4.36 | 2.54 | 6.70 | .00 | 81.07 | .02· | .47*** | .13*** | .04** | 1.00 | | | | | | | | | | | | | |
| 6. Follower–brand fit | .08 | .07 | .09 | .00 | .50 | -.01 | .01 | -.17*** | -.12*** | -.11*** | 1.00 | | | | | | | | | | | | |
| 7. Post positivity | .28 | .31 | .42 | -.90 | .95 | .02 | -.01 | -.10*** | -.06*** | -.07*** | .06*** | 1.00 | | | | | | | | | | | |
| 8. Sponsor salience | .61 | .00 | .86 | .00 | 10.00 | .07*** | .09*** | -.15*** | -.06*** | .05*** | .00 | .05*** | 1.00 | | | | | | | | | | |
| 9. New product launch | .10 | .00 | .30 | .00 | 1.00 | .00 | .04** | -.12*** | -.05*** | -.05*** | .13*** | -.02· | .05*** | 1.00 | | | | | | | | | |
| 10. Promotion | .18 | .00 | .38 | .00 | 1.00 | .04*** | .07*** | -.14*** | -.08*** | .02· | .00 | .12*** | .28*** | -.02· | 1.00 | | | | | | | | |
| 11. Post length | 96.58 | 100.00 | 48.72 | 4.00 | 576.00 | .04** | .17*** | -.43*** | -.27*** | -.05*** | .24*** | .08*** | .36*** | .19*** | .27*** | 1.00 | | | | | | | |
| 12. Post number in campaign | 47.44 | 14.00 | 70.88 | 1.00 | 265.00 | -.01 | -.12*** | .24*** | .11*** | .00 | -.10*** | .16*** | -.07*** | -.11*** | -.04** | -.36*** | 1.00 | | | | | | |
| 13. Service (vs. product) brand | .21 | .00 | .41 | .00 | 1.00 | .03** | .11*** | -.03* | -.08*** | .16*** | -.17*** | -.06*** | .14*** | -.15*** | .16*** | .07*** | -.06*** | 1.00 | | | | | |
| 14. Premium (vs. value) brand | .12 | .00 | .33 | .00 | 1.00 | .00 | .04** | -.14*** | -.07*** | -.09*** | .10*** | .04** | -.05*** | .14*** | -.02 | .18*** | -.14*** | -.09*** | 1.00 | | | | |
| 15. Foreign (vs. local) brand | .34 | .00 | .47 | .00 | 1.00 | .00 | .03* | -.19*** | -.08*** | -.11*** | .10*** | .02· | .02 | .09*** | .05*** | .28*** | -.08*** | -.33*** | .36*** | 1.00 | | | |
| 16. Influencer gender | .64 | 1.00 | .48 | .00 | 1.00 | -.01 | -.02· | -.10*** | -.08*** | -.08*** | .10*** | .02 | -.07*** | -.01 | .02 | .08*** | -.03* | -.12*** | .05*** | .16*** | 1.00 | | |
| 17. Golden week | .08 | .00 | .27 | .00 | 1.00 | -.01 | -.07*** | .17*** | .10*** | .01 | -.03** | -.03* | -.08*** | -.08*** | -.09*** | -.18*** | .07*** | -.06*** | -.05*** | -.09*** | .00 | 1.00 | |
| 18. Weekend | .26 | .00 | .44 | .00 | 1.00 | .02 | -.01 | .00 | -.02 | -.01 | .01 | -.01 | .00 | -.02 | .04*** | -.03* | .01 | .00 | -.02 | -.01 | -.02· | .10*** | 1.00 |

*Note*: The statistics are reported based on the original values of variables (i.e., without taking natural logarithms).
*** $p < .001$, ** $p < .01$, * $p < .05$, · $p < .10$.

**TABLE 4**
**FIRST-STAGE SELECTION MODEL**

| Independent Variables | Influencer Selection (1 = selection) |
|---|---|
| Similar influencer selection (1 = selection) | 1.646*** |
| | (.018) |
| Increasing trend in influencer activity | .030 |
| | (.024) |
| Influencer gender (1 = female) | .069*** |
| | (.010) |
| Influencer activity | < .001 |
| | (< .001) |
| Follower size | .011*** |
| | (< .001) |
| Constant | -2.980*** |
| | (.009) |
| Number of observations | 2,076,732 |

*Note*: Standard errors are reported in parentheses.
*** $p < .001$, ** $p < .01$, * $p < .05$, · $p < .10$.

# TABLE 5
# HYPOTHESIS TESTS: SECOND-STAGE ENGAGEMENT MODEL AND NONLINEAR MODERATING EFFECTS

| Variables | | Model 1 | Model 2 | Model 3a | Model 3b | Model 3c | Model 3 |
|---|---|---|---|---|---|---|---|
| **Independent Variable** | | | | | | | |
| ln(Influencer marketing spend) ($ IMS) | | .457*** | .143· | .076 | .098 | .183* | .072 |
| | | (.027) | (.080) | (.081) | (.081) | (.082) | (.084) |
| **Interaction Terms** | | | | | | | |
| ***Sender (Influencer) Characteristics*** | | | | | | | |
| Influencer activity × ln($ IMS) | | | .006*** | .020*** | .006*** | .006*** | .020*** |
| | | | (.002) | (.003) | (.002) | (.002) | (.003) |
| Influencer activity$^2$ × ln($ IMS) | $H_1$ (∩) | | | -.001*** | | | -.001*** |
| | | | | (<.001) | | | (<.001) |
| Influencer originality × ln($ IMS) | $H_2$ (+) | | .592*** | .561*** | .594*** | .593*** | .565*** |
| | | | (.114) | (.113) | (.114) | (.114) | (.113) |
| Follower size × ln($ IMS) | $H_3$ (+) | | .019*** | .010** | .019*** | .019*** | .010** |
| | | | (.003) | (.003) | (.003) | (.003) | (.003) |
| ***Receiver (Follower) Characteristics*** | | | | | | | |
| Follower-brand fit × ln($ IMS) | | | -.431 | -.395 | 1.411* | -.444· | 1.358* |
| | | | (.268) | (.265) | (.652) | (.268) | (.644) |
| Follower-brand fit$^2$ × ln($ IMS) | $H_4$ (∩) | | | | -8.185** | | -7.825** |
| | | | | | (2.647) | | (2.612) |
| ***Message (Post) Characteristics*** | | | | | | | |
| Post positivity × ln($ IMS) | | | -.087· | -.064 | -.087· | -.007 | .017 |
| | | | (.049) | (.048) | (.049) | (.060) | (.059) |
| Post positivity$^2$ × ln($ IMS) | $H_5$ (∩) | | | | | -.250* | -.250* |
| | | | | | | (.108) | (.107) |
| Sponsor salience × ln($ IMS) | $H_6$ (+/–) | | .092*** | .100*** | .097*** | .087** | .100*** |
| | | | (.028) | (.027) | (.028) | (.028) | (.027) |
| New product launch × ln($ IMS) | $H_7$ (+/–) | | -.488*** | -.441*** | -.501*** | -.475*** | -.440*** |
| | | | (.070) | (.069) | (.070) | (.070) | (.070) |
| **Moderators** | | | | | | | |
| Influencer activity | | -.036*** | -.055*** | -.177*** | -.055*** | -.055*** | -.177*** |
| | | (.002) | (.007) | (.015) | (.007) | (.007) | (.015) |
| Influencer activity$^2$ | | | | .001*** | | | .001*** |
| | | | | (<.001) | | | (<.001) |
| Influencer originality | | -2.043*** | -5.213*** | -4.991*** | -5.224*** | -5.212*** | -5.002*** |
| | | (.184) | (.682) | (.675) | (.681) | (.682) | (.675) |
| Follower size | | .010 | -.159*** | -.080** | -.161*** | -.159*** | -.081** |
| | | (.006) | (.028) | (.029) | (.028) | (.028) | (.029) |
| Follower-brand fit | | .020 | 2.051 | 1.865 | -8.579* | 2.134 | -7.893* |
| | | (.451) | (1.625) | (1.606) | (3.980) | (1.625) | (3.930) |
| Follower-brand fit$^2$ | | | | | 47.624** | | 44.091** |
| | | | | | (16.268) | | (16.058) |
| Post positivity | | .013 | .463 | .294 | .459 | .052 | -.118 |
| | | (.090) | (.290) | (.287) | (.290) | (.354) | (.349) |
| Post positivity$^2$ | | | | | | 1.306* | 1.299* |
| | | | | | | (.649) | (.641) |
| Sponsor salience | | .009 | -.561** | -.609*** | -.588*** | -.528** | -.599*** |
| | | (.046) | (.178) | (.176) | (.178) | (.179) | (.177) |
| New product launch (1 = yes) | | .302* | 3.224*** | 2.907*** | 3.337*** | 3.139*** | 2.925*** |
| | | (.128) | (.445) | (.440) | (.447) | (.447) | (.444) |
| **Control Variables** | | | | | | | |
| Promotion (1 = yes) | | .075 | .136 | .133 | .142 | .141 | .144 |
| | | (.101) | (.100) | (.099) | (.100) | (.100) | (.099) |
| Post length | | .012*** | .011*** | .009*** | .011*** | .011*** | .009*** |
| | | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| Post number in campaign | | -.007*** | -.007*** | -.006*** | -.007*** | -.007*** | -.006*** |
| | | (<.001) | (<.001) | (<.001) | (<.001) | (<.001) | (<.001) |
| Service brand (1 = yes) | | .491* | .626** | .823*** | .637** | .639** | .847*** |
| | | (.241) | (.240) | (.237) | (.240) | (.240) | (.237) |
| Premium brand (1 = yes) | | .147 | -.010 | -.031 | <.001 | -.013 | -.029 |
| | | (.127) | (.126) | (.125) | (.126) | (.126) | (.125) |
| Foreign brand (1 = yes) | | -.059 | -.043 | -.098 | -.052 | -.032 | -.096 |
| | | (.101) | (.102) | (.101) | (.102) | (.102) | (.101) |
| Influencer gender (1 = female) | | .158* | .205** | .277*** | .210** | .198* | .274*** |
| | | (.078) | (.077) | (.077) | (.077) | (.077) | (.077) |
| Golden week (1 = yes) | | -1.006*** | -.901*** | -.869*** | -.897*** | -.896*** | -.860*** |
| | | (.141) | (.139) | (.138) | (.139) | (.139) | (.138) |
| Weekend (1 = yes) | | .048 | .042 | .024 | .034 | .043 | .019 |
| | | (.083) | (.082) | (.081) | (.082) | (.082) | (.081) |
| Inverse Mills ratio | | <.001 | -.016 | -.007 | -.014 | -.018 | -.008 |
| | | (.062) | (.061) | (.061) | (.061) | (.061) | (.061) |
| Constant | | 2.357*** | 4.415*** | 5.187*** | 4.642*** | 4.230*** | 5.221*** |
| | | (.329) | (.549) | (.549) | (.554) | (.558) | (.562) |
| Brand category-fixed effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | | 5,835 | 5,835 | 5,835 | 5,835 | 5,835 | 5,835 |
| Adjusted R-square | | .421 | .435 | .450 | .436 | .436 | .451 |
| AIC | | 28171 | 28030 | 27882 | 28024 | 28028 | 27874 |
| BIC | | 28491 | 28397 | 28262 | 28404 | 28408 | 28281 |

*Notes*: Standard errors are reported in parentheses. *** $p < .001$, ** $p < .01$, * $p < .05$, · $p < .10$.

**FIGURE 1**
**CONCEPTUAL FRAMEWORK OF INFLUENCER MARKETING EFFECTIVENESS**

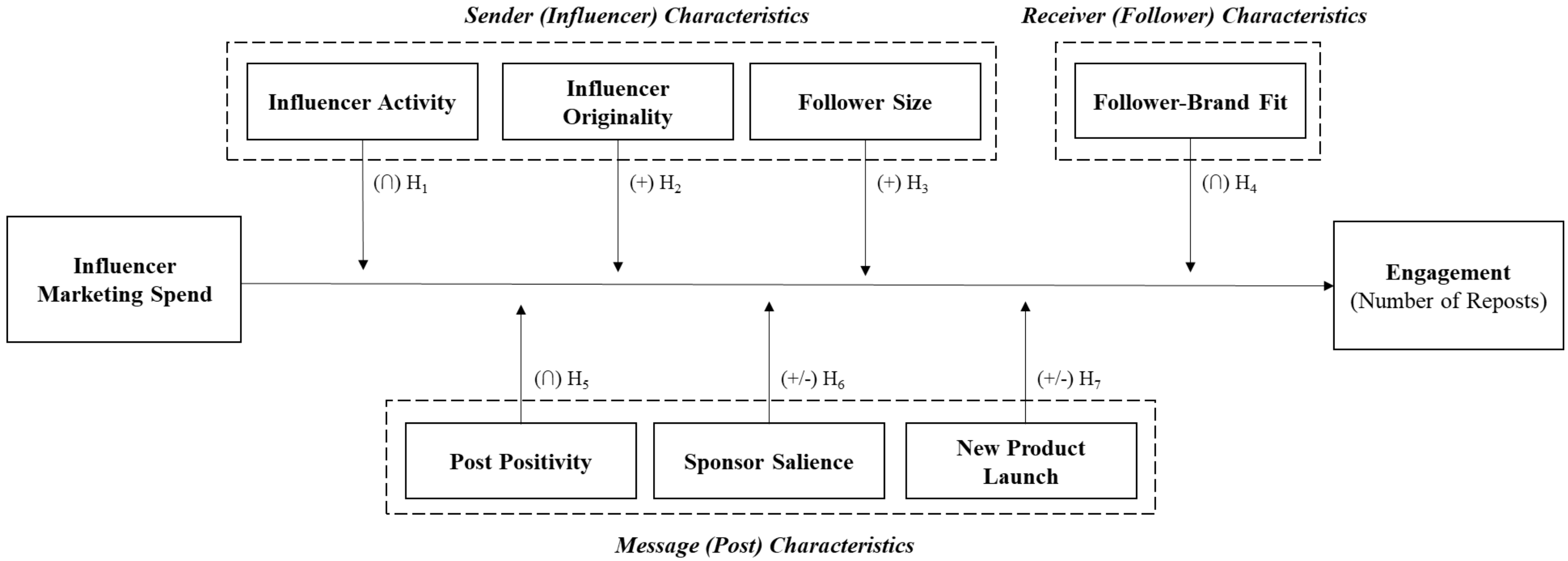
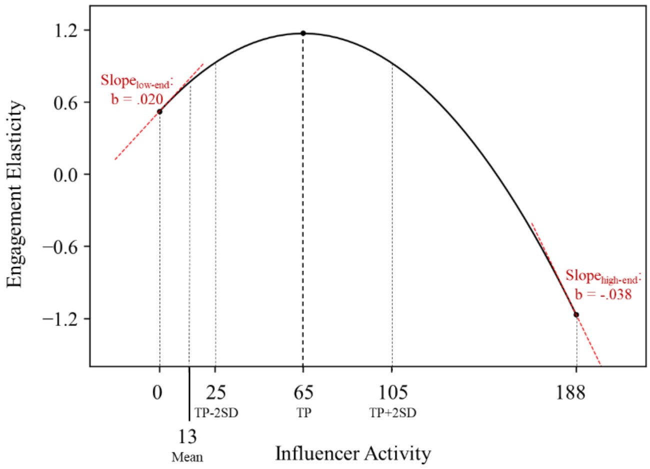
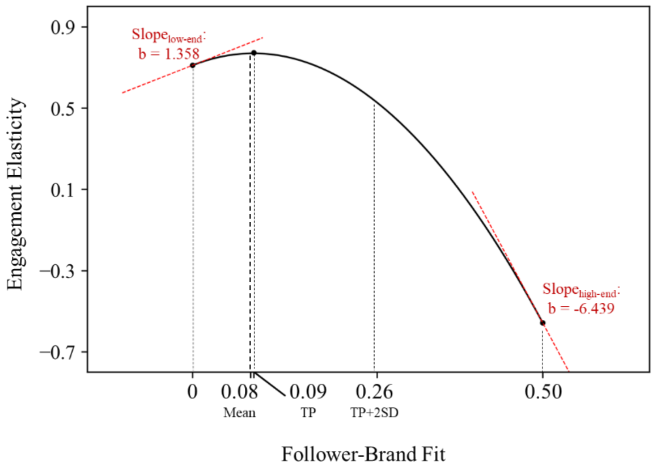


**FIGURE 2**
**NONLINEAR MODERATING EFFECTS ON INFLUENCER MARKETING ELASTICITY**

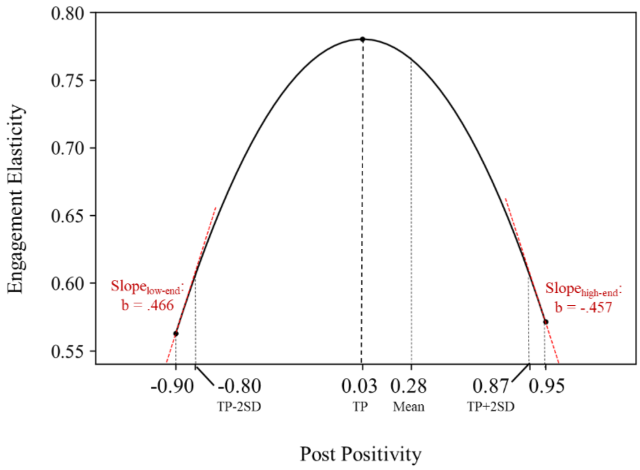
A: Nonlinear Moderating Effect of Influencer Activity




B: Nonlinear Moderating Effect of Follower–Brand Fit




C: Nonlinear Moderating Effect of Post Positivity




*Notes: TP* denotes turning point, and *SD* denotes standard deviation.