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Brand engagement on social media: will firms’ social media efforts influence search engine advertising effectiveness?

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ABSTRACT
Although firms leverage social media platforms such as Facebook to engage with customers, they often treat social media elements and other online marketing activities such as search engine advertising as stand-alone, rather than part of an integrated online activities system. Hence, it is important to systematically understand how specific elements of social media, signifying and representing behavioural manifestations of brand engagement, relate to other online activities. We study how three types of brand engagement on social media – affiliation, conversation and responsiveness – influence search engine advertising effectiveness, including click-through rate and conversion rate. Specifically, we find that affiliation, conversation and responsiveness increase click-through rate and conversion rate. Moreover, brand engagement on social media strengthens the relationships between advertisement rank and search engine advertising effectiveness.

INTRODUCTION
Marketing executives and brand managers have a long-standing interest in engaging with consumers through social media (De Vries, Gensler, & Leeflang, 2012). Such efforts are defined as building brand engagement on social media, which refers to the interactive behaviours among consumers and brands. Consequently, according to a recent US survey of 351 marketing executives, spending on social media platforms now represents 9% of marketing budgets1 (Tadena, 2014). From a consumer’s point of view and compared to traditional media, social media provides a platform for two-way dialogue between consumers and brands; it also provides a means to seek and discover new brands, compare alternative brands and read comments and reviews from other consumers.

Firms’ efforts in engaging with customers through social media have gained increasing attention from academic researchers. Some research has demonstrated the critical role of engagement with consumers through social media (Habibi,
Laroche, & Richard, 2014; Hollebeek, Glynn, & Brodie, 2014; Lin, Ross, & Liu, 2015). For example, Lin et al. (2015) find that brand engagement on social media is positively associated with a firm’s financial performance. Hollebeek et al. (2014) show that consumer engagement in social media can increase self-brand connection and brand usage intent. However, there is scant research investigating relationships between brand engagement on social media and online advertising. Although research has linked some types of engagement to online banner advertising (e.g. Calder, Malthouse, & Schaedel, 2009), it has not explored how engagement via online social media platforms influences online advertising effectiveness, specifically search engine advertising. Search engine advertising is the predominant form of online advertising (Rutz & Bucklin, 2011). It is a service offered by Internet search engines through which advertisers select specific keywords and create textual advertising based on consumers’ search entries.

It should be noted that marketers recognise that they face a similar problem: in the same survey of marketing executives, only 15% of marketers claimed that they can show the impact of social media on their businesses (Tadena, 2014). There is evidence that, as firms continue to leverage online media to better reach and engage with customers, they often treat social media platforms (e.g. Facebook) and other online marketing strategies (e.g. search engine advertising) as stand-alone elements, rather than part of an integrated system (Hanna, Rohm, & Crittenden, 2011). Therefore, we ask: how does brand engagement on social media influence the effectiveness of search engine advertising?

To explore the relationship between brand engagement on social media and search engine advertising effectiveness, we collected industry data from two different sources: brand engagement data from Facebook and search engine advertisement data from Google. We examined two outcomes for search engine advertisements: (1) click-through rate, a measure of the degree to which consumers’ attention was attracted by the ad; and (2) conversion rate, a measure of the sales return from the advertisement. Results show that brand engagement on social media positively influences the effectiveness of search engine advertising (i.e. click-through rate and conversion rate). We also find that brand engagement on social media amplifies the positive effect of a top advertisement rank on search engine advertising effectiveness.

Our study contributes to academic research in several ways. First, we contribute to research on engagement. Concepts related to ‘engagement’ are gaining popularity in the marketing literature, reflected by a wide range of concepts: consumer engagement (e.g. Brodie, Hollebeek, Juric, & Ilic, 2011; Brodie, Ilic, Juric, & Hollebeek, 2013); consumer brand engagement (e.g. Hollebeek, 2011a, 2011b; Hollebeek et al., 2014); brand engagement in self-concept (Sprott, Czellar, & Spangenberg, 2009); online engagement (Calder et al., 2009); and brand community engagement (e.g. Algesheimer, Dholakia, & Herrmann, 2005; Baldus, Voorhees, & Calantone, 2015; Habibi et al., 2014). Despite significant interest in engagement, there is limited research examining consumer–brand relationships in social media. We contribute to this stream of literature by providing a lens through which to view and measure the relationship between brand engagement on social media and search engine advertising. Specifically, we identify three dimensions of brand engagement on social media – affiliation, conversation and responsiveness – and demonstrate that both consumer-initiated
social media engagement efforts (i.e. affiliation and conversation) and firm-initiated engagement efforts (i.e. responsiveness) are important in influencing search engine advertising effectiveness.

Second, we contribute to the literature on search engine advertisement rank. A growing body of research has examined the effect of search engine advertisement rank on advertisement performance. These studies indicate that the lower (better) the rank of the advertisement in the search list, the higher is the advertisement’s click-through rate and/or conversion rate, and that the effect of rank can be influenced by: keyword characteristics (Ghose & Yang, 2009; Rutz, Trusov, & Bucklin, 2011; Yang & Ghose, 2010); the advertisers’ positioning strategy (Animesh, Viswanathan, & Agarwal, 2011); and consumers’ knowledge and beliefs about firm qualities (Jerath, Ma, Park, & Srinivasan, 2011). We extend this line of work by examining the moderating role of brand engagement on social media on the relationship between search engine advertisement rank and advertisement performance.

Finally, our findings offer practical managerial advice. Overall, we provide evidence that brand engagement on social media and online advertising such as search engine advertising should not be considered independent marketing tools, but part of an integrated online marketing strategy (Hanna et al., 2011). Specifically, we provide firms and managers with three different ways – affiliation, conversation and responsiveness – to understand, and measure their level of brand engagement on social media. In turn, this provides a basis that helps managers better understand how their social media efforts relate to search engine advertising. For instance, if a firm has a limited advertising budget and cannot pay for a higher rank in search engine advertising, they could invest in social media such as Facebook to facilitate interaction between their brand(s) and consumers. In turn, these efforts can improve search engine advertising effectiveness. Overall, the contributions of our study are threefold: (1) we contribute to the strong and growing literature related to brand and consumer engagement (e.g. Hollebeek, 2011a, 2011b; Hollebeek et al., 2014); (2) we contribute to the literate related to search engine advertising and (3) we provide practical managerial advice on how to leverage social media to boost the effectiveness of search engine advertising.

In the next section, we provide an overview of brand engagement on social media, introduce search engine advertising and discuss the theoretical background about how brand engagement on social media should influence search engine advertising effectiveness. After presenting the data, methodology and results, we conclude with a discussion of managerial implications and suggestions for future research.

**Theoretical background**

Marketing literature has demonstrated that the Internet has fundamentally changed the way consumers generate and obtain consumption-related information. In particular, consumers rely on various Internet-based information sources to make purchase decisions (Anderson & Palma, 2012; Ghose, Ipeirotis, & Li., 2014), including using social media platforms’ brand-related content with others (Xiang & Gretzel, 2010), and using search engines to obtain brand-related information (Xiang, Wöber, & Fesenmaier, 2008). Consequently, firms have increasingly invested in multiple online marketing channels, including social media and search engine advertising. Research also suggests that the
relationship between social media and search engines is evolving in how one influences the other (Blackshaw & Nazzaro, 2006; Gretzel, 2006; Xiang & Gretzel, 2010). Thus, the major goal of this study is to explore how brand engagement on social media impacts the effectiveness of search engine advertising.

Next, we discuss brand engagement on social media, followed by a discussion on how three dimensions of brand engagement on social media (i.e. affiliation, conversation and responsiveness) are associated with search engine advertisement performance.

**Brand engagement on social media**

Brand engagement on social media stems from a multidisciplinary theoretical perspective – including marketing (Lin et al., 2015), sociology (Bourdieu, 1986), psychology (Achterberg et al., 2003) and information systems (Millen & Patterson, 2002) – and from marketing practice (Weinberg & Pehlivan, 2011; Zinnbauer & Honer, 2011). The practical foundation of brand engagement on social media draws from a concept known as ‘social currency’, the extent to which people share brand-related information with others as part of their everyday social lives (Zinnbauer & Honer, 2011). The primary theoretical foundation of brand engagement on social media originates from Bourdieu’s social capital theory, which suggests that social networks have a range of value, and are dependent upon network size, and interactivity (Bourdieu, 1986; Zinnbauer & Honer, 2011).

Complementing this line of work, and underscoring the importance of interactivity, research in psychology and information systems recognises the importance of stimulating engagement in social contexts (i.e. involvement with social activities and interactions) in contexts such as online community networks (Achterberg et al., 2003; Millen & Patterson, 2002; Zhang, Jiang, & Carroll, 2011). For example, Zhang et al. (2011) find that social engagement, defined as ‘the commitment of a member to stay in the group and interact with other members’ reinforces social identities and social capital with the affordances of Facebook. In addition, Millen and Patterson (2002) suggest that creating online mechanisms that facilitate conversations also stimulates interactivity. Consistent with this work, brand engagement on social media extends the practical application of social currency by capturing how consumers interact with other consumers and brands in discussing a brand in online social platforms. Formally, and paralleling previous engagement research (Gummerus, Liljander, Weman, & Pihlström, 2012; Van Doorn et al., 2010), we define brand engagement as the customers’ behavioural manifestation towards a brand – beyond purchase – resulting from motivational drivers, which is captured through the interactive behaviours between consumers and brands. While we recognise that this definition applies to both online and offline contexts, we draw specific attention to brand engagement on social media which captures the extent to which people use social media to engage with brands and interact with other consumers as part of their everyday lives.

Brand engagement on social media parallels a wide range of work related to engagement (Brodie et al., 2013; Hollebeek et al., 2014). According to Hollebeek et al. (2014), there are many engagement-based concepts, reflecting the nascent developmental state of engagement research in marketing. Broadly, engagement
concepts such as consumer brand engagement, represent a two-way interaction between a customer and an engagement object (e.g. brand, firm) and are characterised by specific levels of cognitive, emotional and behavioural activities (Hollebeek, 2011a). In this research, and consistent with previous works (Gummerus et al., 2012; Van Doorn et al., 2010), we focus on brand engagement in a specific context, social media, and focus on the behavioural manifestations of brand engagement. According to Gummerus et al. (2012), this type of customer engagement is directly related to the emergence of new media, which recognises that consumers carry out a number of brand-related behaviours that did not exist a decade ago, such as online discussions, and participating in online brand communities.

As depicted in Table 1, few studies have focused on engagement in an online context, such as online websites (Calder et al., 2009), social media (Hollebeek et al., 2014) and online brand communities (Gummerus et al., 2012). Moreover, and with

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<th>Author(s)</th>
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<td>This article</td>
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<td>Firm- and consumer-initiated</td>
<td>Social media</td>
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<td>Baldus et al. (2015)</td>
<td>Online brand community engagement</td>
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Note: Focal research contexts marked with ‘–’ denotes that no specific research context existed.
one exception (Van Doorn et al., 2010), previous research has not considered brand engagement from both a consumer-initiated and a firm-initiated perspectives. In a theoretical overview of customer brand engagement, Van Doorn et al. (2010) emphasise the notion that firms can engage customers by utilising online social platforms to encourage behavioural expressions that reflect customer engagement. According to Van Doorn et al. (2010), firms can influence consumers’ engaging behaviours by developing online platforms that entice engagement. Indeed, several studies demonstrate how social media, such as Facebook, can be leveraged to foster customer engagement behaviours (Ashley & Tuten, 2015; Kabadayi & Price, 2014). Our study is the first to specifically address this idea by considering how customers engage with brand-related content that is produced and initiated by the firm. In addition, while brand engagement on social media does not capture the thoughts and feelings a brand may evoke in individuals (Hollebeek et al., 2014), it does capture brand-related behavioural interactivity from an individual perspective and brand perspective. Overall, brand engagement on social media signifies specific, interactive behaviours among consumers and brands in a social media context.

Prior research focuses on consumers’ perceptions of engagement and relies primarily on survey research (Hollebeek et al., 2014). In particular, Hollebeek et al. (2014) develop a scale that measures three dimensions of consumer brand engagement on social media, including cognitive processing (e.g. interest in using social media), affection (e.g. feeling about using social media) and activation (e.g. behaviours related to social media use). Our study complements this work by showing how industry data can be leveraged to measure different types of consumer-initiated and firm-initiated brand engagement behaviours on social media. Our work is also consistent with more recent work that demonstrates the use of industry data to measure types of brand and consumer engagement (e.g. Ashley & Tuten, 2015; Brodie et al., 2013; Malhotra, Malhotra, & See, 2013; Miller & Tucker, 2014). Next, we discuss the details of each dimension of brand engagement on social media.

Derived from the concept of brand community (McAlexander, Schouten, & Koenig, 2002; Muniz & O’Guinn, 2001), affiliation, a consumer-initiated action, is defined as the brand-related connections among consumers. Today, consumers are becoming increasingly interested in the social status that derives from brand affiliations (Fournier & Lee, 2009). In online social platforms, every time a consumer becomes a fan of a brand (e.g. a Facebook fan page), the brand gets additional exposure to and affiliation with that consumer and other consumers.

There are several concepts that although they are distinct relative to affiliation, they have conceptual similarities. For example, there are similarities to Hollebeek et al. (2014)’s construct named affection, which captures the emotional interaction between a consumer and a brand. Because of its focus on overt behaviours, affiliation focuses more on how a consumer uses a brand as an instrument to interact with other consumers. Thus, affection may represent an antecedent variable of affiliation. Another similar construct with affiliation is identification, which refers to an employee’s sense of closeness to an institution (Ashforth & Mael, 1989). Identification serves as a salient identity that may form part of the identity-based motivation of employee engagement (He, Zhu, & Zheng, 2014; Saks, 2006). Therefore, identification may also represent a key
emotional antecedent condition that enables individuals to become behaviourally affiliated with an organisation (Ashforth & Mael, 1989).

Based on social capital theory (Bourdieu, 1986; Zinnbauer & Honer, 2011), conversation, also a consumer-initiated action, refers to brand-related talk and brand-supporting actions among consumers. Overall, conversation captures information being shared within a consumer group (Brown, Barry, Dacin, & Gunst, 2005; Keller, 2010). Consumers can voice their opinions and experiences related to the firm with other social media users, creating social interactions on social media (Agarwal, Animesh, & Prasad, 2009). A similar construct with conversation is electronic word-of-mouth (e-WOM). e-WOM refers to ‘any positive or negative statement made by potential, actual or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet’ (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004, p. 39). But while conversation occurs only on social media sites, eWOM can take place through other online channels, such as emails, forums, instant messaging, blogs and product review sites (Vilpponen, Winter, & Sundqvist, 2006). Moreover, a conversation initiated by consumers could be positive, negative or neutral, without any purposeful influencing activity (Kabadayi & Price, 2014; Naylor, Lamberton, & West, 2012); whereas consumers’ eWOM tends to influence others’ attitudes and behaviours (Chu & Kim, 2011).

Finally, responsiveness, a firm-initiated consumer engagement, captures how engaged consumers respond to firm-initiated and firm-generated content on social media. When a consumer responds to firm-initiated content on a brand’s social media page, anyone who views the brand’s social media page can see the responsive activities, even though the viewers are not the consumer’s personal friend on social media. By responding to firm-initiated and firm-generated content on social media, a consumer can strengthen their personal relationship with the brand (Rishika, Kumar, Janakiraman, & Bezawada, 2013). For instance, responsiveness provides a platform to view other consumers’ opinions and experiences, which in turn affects consumers’ relationship intensity with the brand (McAlexander et al., 2002).

Overall, prior research demonstrates that brand engagement is related to several online contexts and behaviours, including for example: a brand community (Trusov, Bucklin, & Pauwels, 2009); conversation (Miller & Tucker, 2014) and consumer interaction with a firm brand page (Rishika et al., 2013). However, previous research has not systematically examined the differential effects of brand engagement on social media on paid search advertising effectiveness. As such, and consistent with previous works (Lin et al., 2015; Miller & Tucker, 2014; Rishika et al., 2013; Trusov et al., 2009)), we conceptualise three dimensions – affiliation, conversation and responsiveness – that capture both consumer-initiated and firm-initiated brand engagement on social media efforts and study how these types of brand engagement influence search engine advertising effectiveness.

**Search engine advertising**

With the prominence of search engines, such as Google and Yahoo!, search engine advertising is a dominant form of online advertising. Among various online advertising
formats, search engine advertising accounts for nearly 40% of online advertising spending (Agarwal, Hosanagar, & Smith, 2011). Overall, search engine advertising is considered to be an inexpensive and scalable form of internet marketing, and is considered to be one of the best ways to draw visitors to an advertiser’s website (Karjaluoto & Leinonen, 2009; Rangaswamy, Giles, & Seres, 2009).

The process of data generation for search engine advertising is different from that for traditional offline advertising. In search engine advertising, advertisers bid on keywords in the auction process. Paid-search results are rank-based, dependent on whether and how much a firm bids for the keywords relevant to the search query. The higher the price an advertiser bids for a keyword, the better (lower) the rank for the search engine advertisement. Once the advertisers get a rank for the keywords, the advertisements are displayed on the search pages in response to consumers’ queries.

The serving of the advertisement in response to a query for a keyword is called an impression. If the consumer clicks on the ad, which is denoted as a click, he/she will be led to the landing page of the advertiser’s website. If the consumer purchases products or services from the advertiser’s website, a conversion is recorded. In general, there are two indicators of effectiveness for search engine advertisements: click-through rate, and conversion rate (Ghose & Yang, 2009). Following previous literature (e.g. Ghose & Yang, 2009), conversion rate is defined as the ratio of the number of conversions to the number of clicks, and click-through rate is the ratio of the number of clicks for a specific advertisement to the number of impressions of the advertisement. Figure 1 summarises the process of paid search advertising.

Generally, click-through rate and conversion rate are low (Rutz & Trusov, 2011). This is due, in part, to an overload of online information, and the observation that consumers spend very limited time (e.g. only a few seconds) actually looking at content a website before clicking through to the next site; overall, this notion refers to thin-slice judgments which reflect consumers’ automatic and quick responses to Internet content (Peracchio & Luna, 2006). Thus, click-through rate and conversion rate are distinct from brand engagement on social media in that they represent consumers’ thin-slice judgment on advertising in a context of search engine advertising. In contrast, brand engagement on social media represents consumers’ time investment in interacting with other consumers and brands (Rothbard, 2001).

Because of the popularity of search engine advertising, researchers have a long-standing interest in studying what drives search engine advertising effectiveness (Agarwal et al., 2011; Ghose & Yang, 2009). To our knowledge, however, research has not investigated how brand engagement on social media influences the effectiveness of

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**Figure 1.** The process of search engine advertising.
search engine advertising or how brand engagement on social media interacts with advertisement rank to impact click-through rate and conversion rate. Next, we discuss these relationships.

**The link between brand engagement on social media and search engine advertising effectiveness**

Previous research demonstrates that some types of engagement are positively associated with advertising effectiveness (Calder et al., 2009; Wang, 2006). Consistent with previous work (Calder et al., 2009), we draw from categorisation theory (Cohen & Basu, 1987) to explain why brand engagement on social media influences consumers’ attitude and behaviour towards the brand’s search engine advertisement. Categorisation is a fundamental cognitive activity which occurs in response to different stimulus situations (Mervis & Rosch, 1981). According to categorisation theory (Cohen & Basu, 1987), consumers’ knowledge about brands forms in structures in their memory. Applied to engagement and advertising effectiveness, the main premise is that contexts with interactive engagements, versus contexts that are not engaging, positively influence advertising effectiveness (Calder et al., 2009; Wang, 2006). For example, Calder et al. (2009) find that consumers’ engagement with a website results in a greater positive attitude towards banner advertisements and more intention to click on the advertisement. According to Dahlén (2005), such a context could serve as a cognitive prime that activates a semantic network of related material that facilitates interpretation of the advertisement. Applied to the context of search engines, if a search engine advertisement evokes knowledge about a brand that includes interactive engagements, there could be a positive relationship between brand engagement on social media and search engine advertising effectiveness.

Relevant to our study is the way in which consumers’ affect or emotional response is associated with the category, such as a specific brand. Fishbein and Ajzen (1975) view people’s attitude towards an object or concept as the location of the object or concept on a dimension of affect. If people identify a new instance as belonging to a category defined previously, their attitudes associated with the previously defined category would be transferred to the new instance (Boush & Loken, 1991; Dahlén, 2005). In this article, we view a brand as a category and the brand’s search engine advertising as a new instance of that brand. A high level of brand engagement on social media ignites consumers’ involvement, attention and elaboration about the brand (Wang, 2006), which would be transferred to the brand’s search engine advertising when consumers see it. The transferred affect associated with the brand’s search engine advertising is likely to increase consumers’ intention to click on the search engine advertisements and make a subsequent purchase.

As a dimension of brand engagement on social media, affiliation refers to the total number of consumers connected to a brand. McAlexander et al. (2002) suggest that brand communities strengthen brand affiliation by providing a specific context and platform for consumers to connect with a specific brand. A brand community is defined as ‘a specialized, non-geographically bound community, based on a structured set of social relationships among admirers of a brand’ (Muñiz & O’Guinn, 2001, p. 4). Research suggests that online brand communities are important because they provide
platforms that facilitate concepts closely related to engagement (Algesheimer et al., 2005). For example, Algesheimer et al. (2005) demonstrate that brand communities are related to engagement; they use a construct of engagement conceptually similar to brand engagement called community engagement, which they define as the consumer’s intrinsic motivation to interact and cooperate with community members. In short, they find that a brand community can foster engagement (Algesheimer et al., 2005). In addition, Gummerus et al. (2012) stress that a brand community, such as a brand’s Facebook page, is an important platform that fosters and captures customers’ engagement behaviours. Gummerus et al. (2012) specifically demonstrate that engagement behaviours, such as liking and creating brand-related posts positively impact brand-related outcomes, including satisfaction and loyalty.

Overall, brand communities provide structure to the relationship between marketers and consumers and facilitate additional marketing functions, such as sharing information, providing assistance and fostering engagement among consumers (Algesheimer et al., 2005; Gummerus et al., 2012; Muñiz & O’Guinn, 2001). Research on brand community suggests that because brand communities increase affiliation, a specific type of brand engagement on social media, it results in consumers having a greater positive affect associated with the community, and as a result, the brand (Algesheimer et al., 2005; Bagozzi & Dholakia, 2006; Gummerus et al., 2012; Martin, Schouten, & McAlexander, 2006; McAlexander et al., 2002; Muñiz & O’Guinn, 2001). This greater positive affect in turn should increase consumers’ likelihood to click on the brand’s search engine advertisements and make a purchase post-click. Thus, we propose that:

**Hypothesis 1:** Affiliation positively influences search engine advertising effectiveness, such that: (H1a) affiliation increases the click-through rate for a brand’s search engine advertisement; and (H1b) affiliation increases the conversion rate for a brand’s search engine advertisement.

Conversation, a consumer-initiated effort, refers to when a consumer ‘talks’ or discusses a brand on social media platforms. Conversation may represent information about products, services, stores and companies (Brown et al., 2005). Research suggests that conversation enhances consumers’ affect, attitudes and behaviours towards a brand (Hansen, 1969; Harvey, 1960; Moschis, 1976; Stafford, 1966; Witt, 1969; Witt & Bruce, 1970). Thus, if consumers are highly engaged in online conversations about a brand, they are more likely to have positive attitudes and behaviours towards the brand’s search engine advertisement. Formally, we propose that:

**Hypothesis 2:** Conversation positively influences search engine advertising effectiveness, such that: (H2a) conversation increases the click-through rate for a brand’s search engine advertisement; and (H2b) conversation increases the conversion rate for a brand’s search engine advertisement.

Responsiveness captures how consumers respond to a brand’s online activities and how they interact with brands on the brand’s social media outlets. Compared to conversation among consumers, responsiveness refers to the interaction between consumers and
Hypothesis 3: Responsiveness positively influences search engine advertising effectiveness, such that: (H3a) responsiveness increases the click-through rate for a brand’s search engine advertisement; and (H3b), responsiveness increases the conversion rate for a brand’s search engine advertisement.

We also suggest that affiliation, conversation and responsiveness moderate the impact of advertisement rank on click-through rate and conversion rate. Previous research shows that online search result ranks influence advertising effectiveness (Pan et al., 2007; Westerwick, 2013). For example, Westerwick (2013) finds that a low (good) search engine ranking increases perceptions of sponsor credibility. In addition, Agarwal et al. (2011) demonstrate that click-through rate decreases as the rank of the advertisement increases (gets worse). Recent studies also show that the degree of attractiveness of the product with the best rank influences consumers, and that advertisement rank influences brand recall (Agarwal et al., 2011). We contend that if consumers are highly engaged in and involved with a brand, a low (good) search engine rank is more likely to influence consumers’ affect and perceptions of sponsor credibility and brand recall. As a result, their likelihood to click on the advertisement and make a purchase will increase. Specifically, a brand with high brand engagement on social media should boost effect of result rank on search engine advertising effectiveness. Formally, we hypothesise that:

Hypothesis 4: Affiliation moderates the relationship between advertisement rank and search engine advertising effectiveness, such that: (H4a) higher (lower) affiliation increases (reduces) the positive effect of a top advertisement rank on the click-through rate; and (H4b) higher (lower) affiliation increases (reduces) the positive effect of a top advertisement rank on the conversion rate.

Hypothesis 5: Conversation moderates the relationship between advertisement rank and search engine advertising effectiveness, such that: (H5a) higher (lower) conversation increases (reduces) the positive effect of a top advertisement rank on the click-through rate; and (H5b) higher (lower) conversation increases (reduces) the positive effect of a top advertisement rank on the conversion rate.

Hypothesis 6: Responsiveness moderates the relationship between advertisement rank and search engine advertising effectiveness, such that: (H6a) higher (lower) responsiveness increases (reduces) the positive effect of a top advertisement rank on the click-through rate; and (H6b) higher (lower) responsiveness increases (reduces) the positive effect of a top advertisement rank on the conversion rate.
Figure 2 depicts our conceptual model, proposing that (1) three dimensions of brand engagement on social media (i.e. affiliation, conversation and responsiveness), (2) are associated positively with search engine advertisement performance and that (3) the effects of advertisement rank are moderated by brand engagement on social media.

**Empirical study**

**Data**

To examine the impact of affiliation, conversation and responsiveness on search engine advertising effectiveness, we collected a comprehensive industry dataset merged from different industry sources, including brand engagement data from a top social network site, *Facebook*, and search engine advertisement data from the world’s most popular search engine, *Google*. There are several reasons to utilise industry data, such as demonstrating the use of ‘real-time’ data in making decisions (Winer, 1999), and moreover, compared to laboratory or survey data, industry data are collected in less obtrusive manners (Houston, 2004).

Industry publications collect firms’ real data on their social media activities to measure engagement. For example in 2009, a leading digital media consultancy *Altimeter Group* and a social content hosting firm *Wetpaint* evaluated and scored the depth of brands’ engagement in social media for the top 100 valued brands in the world. The study measured brands’ engagement based on the data of their actual activities in multiple social media channels, such as publishing social media content, building networks among consumers and updating brand profiles. For instance, *Starbucks* received the highest engagement score among the top 100 brands with nearly 200,000 fans on the official Facebook page. Because of the published content on Facebook and consumer sharing of information, *Starbucks* ‘has built that fan base to
nearly 2.5 million members’ (Elowitz & Charlene, 2009). According to Lee Odden, CEO of Top Rank Online Marketing, consumers’ engagement in brands is typically measured by consumers’ ‘linking, bookmarking, blogging, referring, clicking, friending, connecting, subscribing, submitting inquiry forms and buying’ behaviours (Falls, 2010).

Some academic studies also measure engagement with industry data. According to Gummerus et al. (2012), customer engagement behaviours can be collected unobtrusively by analysing social networking sites, brand communities and other sources. For example, Ashley and Tuten (2015) measured firms’ social media engagement by calculating the number of firms’ Twitter followers and number of Facebook fans, as well as the Klout score from www.klout.com and the engagement score from ENGAGEMENTdb. Brodie et al. (2013) collected consumers’ engagement data by observing users’ real blog activities in an exploratory analysis, such as the length of users’ blog posts and the intervals between their activities. Malhotra et al. (2013) suggest that engagement through Facebook is increasingly critical in marketing, including Facebook fan ‘likes’, comments and shares. Given these trends, we also leveraged industry data to operationalise brand engagement on social media.

We collected brand engagement data from Facebook for a recognised global apparel brand from 1 April 2012 to 1 April 2013. The data were provided by Socialbakers. Facebook is an online social networking site where, among other things, any firm can set up a fan page that enables users to communicate with both the firm and other users of the brand. We gathered data from Facebook to measure three dimensions of brand engagement on social media: affiliation, conversation and responsiveness. Table 2 shows the descriptive statistics for the dimensions. The average daily affiliation is 5218.3, the average daily conversation is 6472.8 and the average responsiveness is 3969.3. Figure 3 displays a representative time-series snapshot of daily levels of affiliation, conversation and responsiveness. As depicted in Figure 3, there is substantial daily variation in the value of affiliation, conversation and responsiveness over time. The greatest activity for both affiliation and conversion was in January 2013, but the greatest activity for responsiveness was in December 2012. In addition, there is day-of-the-week fluctuation in the daily activities of brand engagement on social media for the brand that must be accounted for.

Consistent with previous literature (e.g. Ghose & Yang, 2009; Rutz & Bucklin, 2011; Rutz & Trusov, 2011), we collected search engine effectiveness data for the apparel brand advertisements from Google Adwords from 1 April 2012 to 1 April 2013. Impressions capture how many times an advertisement is seen, that is, how many times the advertisement appears as a result of the search. If a consumer clicks on the advertisement, this denotes a click, resulting in the appearance of a brand landing page for a given website. Further, if the consumer purchases products from the website, a conversion is recorded. We

| Table 2. Descriptive statistics of brand engagement on social media data. |
|-------------------|-------------|---------|---------|---------|
| Variable          | Mean       | SD      | Min.    | Max.    |
| Affiliation       | 5218.3     | 20,115.5| −324    | 304,010 |
| Conversation      | 6472.8     | 5,792.9 | 1698    | 38,261  |
| Responsiveness    | 3969.3     | 1,939.8 | 1708    | 10,097  |
collected data for advertisement effectiveness in daily intervals, including click-through rate, conversion rate and advertisement rank. The data for search engine advertising include 166,344 observations, with 949 unique keywords. Table 3 shows the descriptive statistics for the search engine advertisement data. The average click-through rate is 3.4% and the average conversion rate is 2.3%. The average advertisement rank is 4.2.

**Table 3.** Descriptive statistics of search engine data (\(N = 166,344\)).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Click-through rate</td>
<td>3.4%</td>
<td>13.4%</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>Conversion rate</td>
<td>2.3%</td>
<td>13.6%</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>Advertisement rank</td>
<td>4.2</td>
<td>2.7</td>
<td>0</td>
<td>11</td>
</tr>
</tbody>
</table>

*Figure 3. Daily activities for brand engagement on social media data across time.*
Measures

Measures of brand engagement on social media and search engine advertising performance

Our measures of affiliation, conversation and responsiveness are consistent with previous research (Lin et al., 2015). Affiliation is measured as the daily increase in the number of fans for an official brand page on Facebook. Conversation is measured as the number of individual Facebook users who initially talk about the apparel brand on their own Facebook page each day, such as posting brand-related content, sharing brand-related Facebook posts and tagging brand-related photos on their individual Facebook page. All of these conversations are initiated by the individual Facebook users and are shown on each individual's own Facebook page. Responsiveness is measured as the total number of likes, comments and shares by consumers of the content posted by the brand on the brand's Facebook page and initiated by the brand administrator. Overall, the key difference between conversation and responsiveness is that conversations are shown on each individual's own Facebook page, whereas responses are initiated by a brand administrator and displayed on a brand's Facebook brand page.5

Our measures of advertisement effectiveness and advertisement rank are based on previous search engine advertising work (Ghose & Yang, 2009; Rutz & Bucklin, 2011; Rutz & Trusov, 2011). Recall that advertisement effectiveness refers to the click-through rate and the conversion rate for the advertisement. The click-through rate (CTR) is measured as the ratio of the number of clicks on an advertisement to the number of times the advertisement is shown to consumers (CTR = clicks/impressions). The conversion rate (CONV) is measured as the ratio of the number of purchases that consumers make from the advertisement as a percentage of the number of clicks on the advertisement (CONV = conversions/clicks). Advertisement rank represents how a firm's advertisement ranks against competitors' advertisements, measured as the order in which advertisements appear on the page after a consumer's search query, with lower ranks being better (Table 4).

Table 4. Measurements of variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measurement</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Brand engagement on social media</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affiliation</td>
<td>A daily measure of the increase in the number of daily fans for the official brand page on Facebook each day</td>
<td>Facebook</td>
</tr>
<tr>
<td>Conversation</td>
<td>The number of individual Facebook users who initially talk about the apparel brand on their own Facebook page each day by posting brand-related content, sharing brand-related Facebook posts and tagging brand-related photos on their own Facebook page</td>
<td>Facebook</td>
</tr>
<tr>
<td>Responsiveness</td>
<td>The total number of likes, comments and shares of the content posted by the brand, which are initiated by the brand administrator and displayed on the brand's Facebook brand page</td>
<td>Facebook</td>
</tr>
<tr>
<td><strong>Search engine advertising</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Click-through rate</td>
<td>The ratio of the number of clicks on an advertisement to the number of impressions the advertisement is shown (CTR = clicks/impressions)</td>
<td>Google</td>
</tr>
<tr>
<td>Conversion rate</td>
<td>The ratio of the number of conversions (purchases) that consumers make from the advertisement to the number of clicks on the advertisement (CONV = conversions/clicks)</td>
<td>Google</td>
</tr>
<tr>
<td>Advertisement rank</td>
<td>The order in which advertisements appear on the page after a consumer's search query</td>
<td>Google</td>
</tr>
</tbody>
</table>
Further examination of measures of brand engagement on social media

In this study, we employ industry data to measure marketing constructs. Industry data proxies have become increasingly popular and are strongly preferred over self-report scale measures in disciplines, such as finance, economics, information systems and health care management (Day & Montgomery, 1999; Srivastava, Shervani, & Fahey, 1999). Since there are no other direct industry measures of brand engagement, we followed Lin et al. (2015) and used industry data to measure three dimensions of brand engagement on social media. Aforementioned, each dimension was measured by a single item from industry data.

Despite the advantages of utilizing industry data, there are possible drawbacks related to reliability and validity (Houston & Johnson, 2000). Therefore, we followed Houston’s (2004) suggestion on how to assess reliability and validity of our industry data. However, since one-item data proxies for affiliation, conversation and responsiveness, traditional methods were used, it is not appropriate to assess reliability using traditional methods, such as the use of Cronbach’s alpha, and the use of a confirmatory factor analysis (Houston, 2004). Specifically, we followed Houston (2004)’s suggestions, and collected additional survey data to complement industry data and test the reliability and validity of our measurements. A questionnaire comprising items applied to the apparel firm was administered to a sample of 108 university undergraduate students in September 2015 (46.3% male). Each student was invited to participate in the survey with a university bookstore gift card. All participants were familiar with the apparel firm, and the survey completion time was approximately 5 minutes. Consistent with previous work (Churchill, 1979), two weeks after the initial survey completion, participants were asked to complete the same survey as a post-measure. Although there were two incomplete responses which were omitted from our analysis, all questionnaires were returned to us.

We measured affiliation, conversation and responsiveness using a single item as industry data proxies did. Table 5 contains the item for each construct. To check the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Brand engagement on social media</strong></td>
<td></td>
</tr>
<tr>
<td>Affiliation</td>
<td>I like to become a fan of [the apparel brand] for the official brand page on Facebook</td>
</tr>
<tr>
<td>Conversation</td>
<td>I like to initially talk about [the apparel brand] on my own Facebook page, such as posting content related to [the apparel brand], sharing Facebook posts related to [the apparel brand] and tagging photos related to [the apparel brand] on my own Facebook page</td>
</tr>
<tr>
<td>Responsiveness</td>
<td>I like to respond to the content posted by [the apparel brand] on the brand’s Facebook brand page, such as liking, commenting and sharing the content</td>
</tr>
<tr>
<td><strong>Consumer brand engagement (Hollebeek et al., 2014)</strong></td>
<td></td>
</tr>
<tr>
<td>Cognitive processing</td>
<td>Using [the apparel brand] gets me to think about [the apparel brand]</td>
</tr>
<tr>
<td></td>
<td>I think about [the apparel brand] a lot when I’m using it</td>
</tr>
<tr>
<td></td>
<td>Using [the apparel brand] stimulates my interest to learn more about [the apparel brand]</td>
</tr>
<tr>
<td>Affection</td>
<td>I feel very positive when I use [the apparel brand]</td>
</tr>
<tr>
<td></td>
<td>Using [the apparel brand] makes me happy</td>
</tr>
<tr>
<td></td>
<td>I feel good when I use [the apparel brand]</td>
</tr>
<tr>
<td></td>
<td>I’m proud to use [the apparel brand]</td>
</tr>
<tr>
<td>Activation</td>
<td>I spend a lot of time using [the apparel brand], compared to other [category] brands</td>
</tr>
<tr>
<td></td>
<td>Whenever I’m using [category], I usually use [the apparel brand]</td>
</tr>
<tr>
<td></td>
<td>[The apparel brand] is one of the brands I usually use when I use [category]</td>
</tr>
</tbody>
</table>
validity of our measures, we also included items that measured consumer brand engagement (Hollebeek et al., 2014). This included three items for cognitive processing, four items for affection and three items for activation (Table 5). All these items were rated on 7-point Likert scales (1 = strongly disagree, 7 = strongly agree).

Table 6 reports reliability and validity statistics for each construct. Because measures of internal consistency reliability, such as Cronbach’s coefficient alpha, cannot be applied to the single-item scales of brand engagement on social media, we employed test–retest reliability for the single-item scales (Heise, 1969). To investigate test–retest reliability, we examined the t-tests of the paired difference between each brand engagement on social media items. The reliability estimate for each construct is: affiliation, 0.94; conversation, 0.91; and, responsiveness, 0.92 (all ps < 0.001), providing evidence for the reliability of our measures of affiliation, conversation and responsiveness.

Second, we assessed nomological validity by calculating correlation coefficients between other relevant constructs (Houston, 2004). Affiliation correlated positively with cognitive processing ($r = 0.82$, $p < 0.01$), affection ($r = 0.86$, $p < 0.01$) and activation ($r = 0.81$, $p < 0.01$); conversation correlated positively with cognitive processing ($r = 0.77$, $p < 0.01$), affection ($r = 0.83$, $p < 0.01$) and activation ($r = 0.75$, $p < 0.01$); and responsiveness correlated positively with cognitive processing ($r = 0.79$, $p < 0.01$), affection ($r = 0.87$, $p < 0.01$) and activation ($r = 0.77$, $p < 0.01$). These results provide support for nomological validity (Stanton, Sinar, Balzer, & Smith, 2002).

Third, we used the traditional multitrait-multimethod (MTMM) approach to assess convergent and discriminant validity (Campbell & Fiske, 1959; Houston, 2004). Table 7

<table>
<thead>
<tr>
<th>Industry data</th>
<th>A</th>
<th>C</th>
<th>R</th>
<th>Survey data</th>
<th>A</th>
<th>C</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affiliation</td>
<td>()</td>
<td></td>
<td></td>
<td>Affiliation</td>
<td>0.29</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Conversation</td>
<td>0.08</td>
<td>()</td>
<td></td>
<td>Conversation</td>
<td>0.06</td>
<td>0.19</td>
<td>0.08</td>
</tr>
<tr>
<td>Responsiveness</td>
<td>0.78</td>
<td>0.38</td>
<td>()</td>
<td>Responsiveness</td>
<td>0.03</td>
<td>0.02</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Note: The validity diagonals are the italicised values. The reliability diagonals are the values in parentheses. Empty parentheses report no appropriate reliability estimates.
illustrates three dimensions of brand engagement, each measured by two methods, generating for separate variables. The entries in the validity diagonal (i.e. the italicised values) are significantly different from zero. Moreover, the entries in the validity diagonal are greater than those lying in corresponding columns and rows in the heterotrait-heteromethod triangles. Further, the entries in the heterotrait-monomethod triangle are greater than those in the heterotrait-heteromethod triangles. These results provide support for convergent and discriminant validity.

**Empirical analyses**

Typically, linear regression models use an ordinary least squares (OLS) approach, which assumes a normal data distribution \( Y \sim N(\mu, \phi) \). However, in search engine advertising data, a normal distribution is inappropriate (Agarwal et al., 2011; Ghose & Yang, 2009). This is because the utility of the individual choice in clicking on an advertisement or converting the advertisement to a sale follows an independent and identically distributed (i.i.d.) extreme value distribution (Agarwal et al., 2011). In other words, two of our dependent variables, click-through rate and conversion rate, are bounded between 0 and 1. Considering this, we use a logit model to capture the click-through probability or conversion probability of a search engine advertisement for a keyword as follows:

\[
Pr = \frac{\exp(U)}{1 + \exp(U)},
\]

where \( U \) is the latent utility of clicking on an advertisement or converting, which depends on brand engagement on social media, advertisement rank and their interactions. We also include indicator variables for day of the week and time trend to control for their effects. The latent utility can be expressed as follows:

\[
U^{CTR} = a_0^{CTR} + \beta_1^{CTR} * Affiliation + \beta_2^{CTR} * Conversation + \beta_3^{CTR} * Responsiveness + \beta_4^{CTR} * Affiliation * Rank + \beta_5^{CTR} * Conversation * Rank + \beta_6^{CTR} * Responsiveness * Rank + \beta_7^{CTR} * Rank + \sum_{d=1}^{6} y_{1d}^{CTR} * Day_d + y_{2}^{CTR} * Time_t + \epsilon^{CTR},
\]

\[
U^{CONV} = a_0^{CONV} + \beta_1^{CONV} * Affiliation + \beta_2^{CONV} * Conversation + \beta_3^{CONV} * Responsiveness + \beta_4^{CONV} * Affiliation * Rank + \beta_5^{CONV} * Conversation * Rank + \beta_6^{CONV} * Responsiveness * Rank + \beta_7^{CONV} * Rank + \sum_{d=1}^{6} y_{1d}^{CONV} * Day_d + y_{2}^{CONV} * Time_t + \epsilon^{CTR},
\]

where CTR, the click-through rate; CONV, the conversion rate; Rank, advertisement rank in the result listing. Top rank is coded as 1; Affiliation, the affiliation dimension of brand engagement on social media; Conversation, the conversation dimension of brand engagement on social media; Responsiveness, the responsiveness dimension of brand engagement on social media; Day, day of week; Time, time trend.
As mentioned previously, click-through rate (CTR) is measured by tabulating the total number of clicks on an advertisement and dividing by the number of impressions for the advertisement; conversion rate (CONV) is measured by taking the total number of conversions/purchases and dividing by the total number of clicks. Advertisement rank represents the daily average rank at which the advertisement is displayed in the search result listing. A lower value for advertisement rank denotes an advertisement that is displayed closer to the top of the search result listings. For example, an advertisement rank of 1 means that the advertisement would be the first listing displayed.

**Estimation results**

**Effects of brand engagement on social media on advertisement effectiveness (hypotheses 1–3)**

Table 8 shows the estimates for the effects of affiliation, conversation and responsiveness on search engine advertising effectiveness, as well as their moderating effects. To test the explanatory power of our model, we compared a full model with three base models. Base model (1) contains only the three dimensions of brand engagement on social media as direct effects and includes day-of-the-week and time trend as our standard control variables. Base model (2) contains only advertisement rank and the control variables. Base model (3) includes the three brand engagement on social media constructs and advertisement rank, as well as the control variables. In the full model, we added the interaction terms between brand engagement on social media and advertisement rank to base model (3). We used the likelihood ratio test to compare the base models against each other and the full model against the base models (Koschate-Fischer, Cramer, & Hoyer, 2014), where the test statistic ($D$) is twice the difference in log-likelihoods ($D = (−2 \ln(likelihood for the null model) − (−2 \ln (likelihood for the alternative model)))$) and follows a chi-squared distribution. Whether the null model is better than the alternative model is determined by the $p$-value of $D$.

Compared with base models (1) and (2), base model (3), which includes both the direct effects of both brand engagement on social media and advertisement rank, leads to a statistically significantly better fit; the likelihood ratio test is statistically significant

<table>
<thead>
<tr>
<th>Variables</th>
<th>Base model (1)</th>
<th>Base model (2)</th>
<th>Base model (3)</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CTR</td>
<td>CONV</td>
<td>CTR</td>
<td>CONV</td>
</tr>
<tr>
<td>Affiliation</td>
<td>−3.8E-7***</td>
<td>3.3E-6***</td>
<td>2.3E-7****</td>
<td>4.0E-6***</td>
</tr>
<tr>
<td>Conversation</td>
<td>3.4E-6***</td>
<td>1.7E-5***</td>
<td>6.7E-7****</td>
<td>2.3E-6***</td>
</tr>
<tr>
<td>Responsiveness</td>
<td>1.3E-4***</td>
<td>6.8E-5***</td>
<td>7.5E-5***</td>
<td>4.0E-5***</td>
</tr>
<tr>
<td>Advertisement rank</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conversation * rank</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Responsiveness * rank</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day of week effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>−4.31***</td>
<td>−1.20***</td>
<td>−1.35***</td>
<td>0.52***</td>
</tr>
<tr>
<td>No. of observations</td>
<td>166,344</td>
<td>166,344</td>
<td>166,344</td>
<td>166,344</td>
</tr>
<tr>
<td>−2 log likelihood</td>
<td>597,400</td>
<td>128,212</td>
<td>375,319</td>
<td>108,631</td>
</tr>
<tr>
<td>AIC</td>
<td>597,422</td>
<td>128,234</td>
<td>375,337</td>
<td>108,649</td>
</tr>
</tbody>
</table>

Notes: ***p < 0.001, **p < 0.01, *p < 0.1.
(ps < 0.001). This indicates that adding the main effects for affiliation, conversation and responsiveness or advertisement rank improves the model fit for search engine advertising effectiveness. Further, the full model, which includes the interaction terms, provides a statistically significant improvement over base model (3) which includes only the direct effects; the likelihood ratio test is significant (ps < 0.001), showing that adding the interaction terms improves the model fit. Moreover, coefficients for the major variables retain their sign and significance across specifications, indicating the robustness of our model.

We find that affiliation exerts a positive and significant effect on both click-through rate (β = 1.4E-10, p < 0.001) and conversion rate (β = 6.4E-6, p < 0.001), suggesting that consumers’ affiliation engagement for the brand enhances both click-through rate and conversion rate. We find that conversation has a positive and significant effect on click-through rate (β = 4.4E-6, p < 0.01) and conversion rate (β = 6.2E-5, p < 0.001), which implies that consumers’ conversation engagement on the brand improves its search engine advertisements’ click-through rate and conversion rate. We also find that the effects of responsiveness on click-through rate (β = 2.6E-4, p < 0.001) and conversion rate (β = 1.6E-4, p < 0.001) are positive and significant, suggesting that consumers’ responsiveness to the brand also improve its advertisements’ effectiveness. Together, these results support H1a, H1b, H2a, H2b, H3a and H3b.

**Moderating effects of brand engagement on social media (hypotheses 4–6)**

We tested the moderating effects of brand engagement on social media by examining the significance of the interaction terms and assessing the effect sizes for the interactions. The results in Table 8 show that the coefficient for the interaction between advertisement rank and affiliation on click-through rate (β = −2.9E-7, p < 0.001) is negative and statistically significant, which implies that higher affiliation strengthens the positive effect of a top advertisement rank on click-through rate. The coefficient for the interaction between advertisement rank and affiliation for conversion rate (β = −2.2E-6, p < 0.1) is also negative and marginally statistically significant. This indicates that higher affiliation helps the effect of a top advertisement rank on conversion rate. Thus, H4a and H4b are supported.

With respect to conversation, the interaction between advertisement rank and conversation has a negative and statistically significant effect for both click-through rate (β = −4.4E-6, p < 0.001) and conversion rate (β = −4.0E-5, p < 0.001). In support of H5a and H5b, this suggests that higher conversation strengthens the positive effect of a top advertisement rank on click-through rate and conversion rate. The coefficients for the interaction between advertisement rank and responsiveness for both click-through rate (β = −1.4E-4, p < 0.001) and conversion rate (β = −1.0E-4, p < 0.001) are negative and statistically significant. This implies that higher responsiveness strengthens the positive impact of a top advertisement rank on advertisement effectiveness. Thus, H6a and H6b are supported.

After testing the significance of the interaction terms, we assessed their effect size ($f^2$) to determine the size of the moderating effects. We use the Cohen effect size formula (Cohen, 1988) to compare the squared multiple correlation ($R^2$) for the full model with $R^2$ for the basic model without interaction terms:
The results show that the full model, including interactions terms between advertisement rank and affiliation, conversation and responsiveness has significantly better explanatory power than the base model without interaction terms ($p < 0.001$). The effect size $f^2$ for the moderating effects is 0.03 for click-through rate and 0.04 for conversion rate. Interaction effect sizes are deemed large if it is 0.35, medium if 0.15 and small if 0.02 (Cohen, 1988). Thus, the moderating effects of affiliation, conversation and responsiveness are significant, with effect sizes that are deemed somewhat larger than small.

**Control variables**
As expected, advertisement rank has a negative and significant effect on click-through rate ($\beta = -0.47, p < 0.001$) and conversion rate ($\beta = -0.42, p < 0.001$), which supports the notion that advertisements displayed in higher positions in the search results positively increase both click-through rate and conversion rate. Also as expected, the results show that the effects of day-of-the-week on click-through rate and conversion rate are significant. This suggests that the likelihood of consumers clicking on an advertisement and that of the following purchase depends to some extent on the day of the week on which they are searching. Further, the effects of time on click-through rate ($\beta = 0.001, p < 0.001$) and conversion rate ($\beta = -0.001, p < 0.001$) are significant, showing that the probabilities of consumers clicking on an advertisement and making a purchase vary across time.

**Robustness checks**
With respect to robustness of the regression results, our main concern was a possible lack of independence between a consumer’s decision to click on a search engine advertisement and their decision to purchase. In other words, are click-through rate and conversion rate correlated? Based on previous works (Agarwal et al., 2011; Ghose & Yang, 2009; Rutz & Trusov, 2011), we correlated the error terms of Equation (2) and (3) to represent their correlations. The following distribution was used:

$$\begin{bmatrix}
\epsilon_{CTR}^R \\
\epsilon_{CONV}^R
\end{bmatrix} \sim \mathcal{N}(0, V), \text{ where } V =
\begin{bmatrix}
V_{11} & V_{12} \\
V_{21} & V_{22}
\end{bmatrix}.$$ (5)

The results of Table 9 provide evidence from estimates of this more structured model. The general insights of the generalised linear model (GLM) results with correlated error terms are similar to that of GLM results without correlated error terms, suggesting that the correlated nature of the dependent variables does not drive our results.

**Tests for alternative explanations**
Previous research questions the quality of social media sites’ data. For instance, Nelson-Field, Riebe, and Sharp (2012) show that the Facebook fan base for two fast moving consumer goods companies is skewed towards the brands’ heavy buyers, but that the actual purchase base is in an opposite pattern for the two brands. This raises an
important question: what supports our findings that brand engagement works in combination with search engine advertising?

One possible explanation is that the user base of search engines is also skewed towards the brands’ heavy buyers. To find evidence with respect to this notion, we separated users of search engines into two categories: users who search for generic products, and users who search specifically for the apparel brand. Rutz and Bucklin (2011) suggest that consumers who search using a generic keyword are not aware that the brand name is relevant to the search, while those who search using a specific branded keyword are aware that the brand is relevant to their current search. Thus, users who search for a generic product are more likely to be non-buyers or light buyers of the brand, whereas users who search for the specific brand are more likely to be moderate to heavy buyers of the brand. To test this, we compared the impressions of non-branded searches with branded searches. The results show a similar negative binomial distribution (NBD)-distributed user base, with high numbers of non-branded searches and much fewer branded searches (see Figure 4). This is consistent with previous literature (Rutz & Bucklin, 2011). Thus, the user base of search engines is

<table>
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<th>Variables</th>
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<th>CONV</th>
</tr>
</thead>
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<tr>
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<td>1.3E-10***</td>
<td>6.4E-6***</td>
</tr>
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<td>Conversation</td>
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<td>2.5E-4***</td>
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<td>Advertisement rank</td>
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<td>-0.42***</td>
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<tr>
<td>Constant</td>
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Notes: ***p < 0.001, **p < 0.01, *p < 0.1.

Figure 4. Search concentration across the search engine searches.
skewed towards non-buyers of the brands, which undermines the plausibility of this possible explanation.

A second explanation is that leveraging social media platforms to engage with heavy buyers of brands also works for non-buyers who start to search the brands in search engines. Therefore, we estimated the effects for how brand engagement on social media impacts search engine advertising effectiveness for two user categories. Table 10 shows that brand engagement on social media has a significant and positive effect on search engine advertising effectiveness for both non-branded and branded searches. The results offer some support for the second alternative explanation that engaging with heavy buyers of the brands in social media platforms also works for their non-buyers in search engines.

### Conclusions, implications and limitations

#### Conclusions and discussion

The results of this study are twofold (see Table 11). First, we show that there is a positive association between brand engagement on social media – affiliation, conversation and responsiveness – and search engine advertising effectiveness. Second, the study reveals that brand engagement on social media moderates the relationship between advertisement rank and search engine advertising effectiveness. In particular, affiliation, conversation and responsiveness amplify the positive effect of a top advertisement rank on search engine advertising effectiveness.

There are three primary implications for the results. The first is that brand engagement on social media can be measured using at least three sub-dimensions, two of which, affiliation and conversation, are consumer-initiated, either purely personal or provided by the brand, and one of which is in response to the brand’s social media activities and take place on the brand’s social media sites. The second is that brand engagement on social media matters to firms’ other online marketing activities. All three aspects of brand engagement on social media have a significantly positive effect on the effectiveness of search advertising and, moreover, positively moderate the effect of a top search advertising rank on the effectiveness of search advertising. Third, these

<table>
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<th>Variables</th>
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<th>Branded searches</th>
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<td>CONV</td>
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<td>−2.04E-6*</td>
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</tr>
<tr>
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<tr>
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</table>

Notes: ***p < 0.001, **p < 0.01, *p < 0.05, "p < 0.1.
results are a first demonstration that the combination of online marketing efforts is more useful than focusing on one to the exclusion of others and that social media is, in fact, a valuable brand management tool.

The results lead us to an additional speculation with respect to types of search engine advertising. In response to a particular keyword search, search engines display two sets of results: a paid search engine advertising list and an unpaid, organic list. While firms can increase the rank of their search engine advertising by bidding more, the rankings of the organic results are based on a complex algorithm devised by the search engines that include the website’s quality and ‘relative importance’ compared to other links (Yang & Ghose, 2010). We might speculate that positive relationships should exist between the level of brand engagement on social media and organic search results for the brand for two different reasons. First, paid search engine advertising and unpaid organic listings are positively correlated with each other’s click-through rate (Yang & Ghose, 2010). We have demonstrated that firms’ efforts on brand engagement on social media are associated with higher click-through and conversion rates for search engine advertising, which may lead to higher click-through and conversion rates of organic listings. Second, and more generally, increased brand engagement on social media and improved search engine advertising’s performance could raise the site’s general popularity or inherent value (Katona & Sarvary, 2010). This would help search engines’ judgment on the site’s quality and importance, thus improving the rank of organic search listings. The click-through rate and the conversion rate of organic search listings would therefore be increased. Overall, these concern merits future consideration.

Managerial implications

In today’s brand management environment, brands engaging with customers through online social platforms have become commonplace. However, what is
the return on this marketing investment? To better measure a return on investment, marketers need evidence linking social media spending to consumer engagement and, ultimately, to brand sales. In addition, search engine advertising is an increasing trend in online advertising spending, not only because of consumers’ increasing usage of search engines, such as Google and Yahoo!, but also because search engine advertising is less costly than traditional media advertising. However, for these two major online activities, little has been known about how social media elements and investments impact search engine advertising effectiveness. Our study addresses this gap by showing that collectively, the dimensions of brand engagement on social media have greater effect on advertising effectiveness compared to each individual dimension.

This study generates several managerial implications. First, firms are increasingly using ‘engagement metrics’ to track their social media activities, but the measurements remain a challenge (Moorman, Ross, & Gorman, 2015). Following Lin et al. (2015) and Gummerus et al. (2012), this study demonstrates that brand engagement behaviours can be collected unobtrusively by analysing social networking sites. We provide firms with three different ways – affiliation, conversation and responsiveness – to understand, and measure their level of brand engagement on social media. This, for example, not only includes how consumers talk about the brand to other consumers, but also how consumers respond to the brand content posted by the company.

Second, Hanna et al. (2011) underscore the notion that social media efforts are part of an online ecosystem – these elements not only relate to, but also often influence, one another. However, results from The CMO Survey referenced previously reveal that firms still manage social media efforts as activities that are separate and distinct from other marketing strategy activities (Moorman, Ross, & Gorman, 2014). In fact, the level of social media integration with marketing strategy has remained both relatively moderate and relatively stable, from 3.8 in 2011 to 3.9 in 2014 (where 1 is ‘not integrated’ and 7 is ‘very integrated’). Our study provides evidence that seemingly unrelated social media investments are, in fact, interdependent activities. Firms’ interactions with customers by way of social media can improve the effectiveness of their online search advertising. In fact, search engines, such as Bing Social Search and TripAdvisor, have begun to integrate richer social information from social media platforms into their ranking mechanism design to improve consumers’ search experience (Ghose, Ipeirotis, & Li, 2012). Our findings offer strong support for firms’ investment in, and perhaps even greater investment in, social media marketing activities (Goh, Heng, & Lin, 2013).

Finally, our findings suggest an alternative means for firms to boost online advertising effectiveness with a limited advertisement budget. Firms with limited budgets that cannot afford to pay for a top advertisement rank search results should consider investing in social media. In turn, these efforts may improve search engine effectiveness. For large firms with considerable resources, boosting brand engagement on social media can amplify the positive impact of bidding for a top advertisement rank on search engine advertising effectiveness. Our findings
offer practical managerial advice for firms that use search engine advertising; these firms should consider hiring employees devoted to attracting and responding to consumers via social media platforms (Tadena, 2014) to increase the performance of their search advertising. In short, firms should continue to utilise social media to provide content and a platform that entices brand engagement among consumers and between the brand and consumers.

Moreover, because responsiveness is a firm-initiated social media action, it can be induced more easily by brand managers compared to consumer-initiated engagement. Thus, firms should invest more in increasing consumers’ engagement using the firms’ social media brand site. For instance, firms can post more news or blogs on their social media platforms and monitor consumers’ responses. Alternatively, firms can generate campaigns (e.g. free products for top answers) to encourage consumer–brand interaction and engagement.

**Limitations and future research**

There are limitations to this study and, consequently, future-research opportunities. First, we relied upon industry data to measure brand engagement on social media. Thus, the nature of our data limits the generalisability of the results of our study. Similarly, it can be argued that the timing of our data, from 2012 to 2013 may limit the generalisability of our results. While this is true for the magnitude of the particular coefficients for the main effects and interactions, it does not apply to the overall results that brand engagement on social media directly affects and also interacts with search advertising rank to affect search advertising effectiveness. There is no reason to suggest that the increasing importance of social media will reduce or eliminate these effects. However, there are additional future research opportunities that may focus on validating our results with additional data sources, perhaps including surveys or experiments. Second, future work should consider applying our framework to the individual level. Third, we relied upon the data of only one brand and one type of social medium (i.e. Facebook) to test our hypotheses. This limits our ability to generalise our results to other brands and social media contexts. For example, how may the use of different social media platforms affect our findings? In addition, what types of engagement behaviour would Twitter foster among consumers? Fourth, in this study we examined only the total numbers for conversation and responsiveness; we did not consider the nature and valence (positive versus negative) of their content. The valence of the content of conversation and responsiveness (i.e. positive versus negative) might have an impact on search engine advertising effectiveness. Future investigation of how the valences of conversation and responsiveness influence search engine advertising effectiveness and other online investments would be useful. Finally, whereas this study provided evidence that firms’ efforts on social media platforms affect their search engine advertising effectiveness, it did not provide a behavioural mechanism to demonstrate why, which also creates an opportunity for future work.
Notes

1. The CMO Survey was compiled by Christine Moorman of Duke University, McKinsey & Co. and the American Marketing Association (AMA). The sample consisted of 351 top marketers from leading organisations in the United States reached through Duke University’s alumni network and the AMA’s membership.

2. Note: In this article, the lower the rank (1–10), the higher the position in the search results. For example, an advertisement rank of 1 means that the advertisement is displayed at the top of the search listing.

3. Socialbakers (http://www.socialbakers.com) is one of Facebook’s preferred marketing developers. It has been awarded three Preferred Marketing Developer badges (Pages, Apps and Insights) from Facebook.

4. One-year historical Google data is sufficient to examine the search engine advertising performance. For example, Ghose and Yang (2009)’s search engine advertising data contain advertising on Google from a large nationwide retail chain during a period of six months in 2007. Rutz and Bucklin (2011)’s data include search engine advertising for a major lodging chain from both Google (from 1 March 2004 to 20 December 2004) and Yahoo! (from 6 May 2004 to 31 August 2004). Rutz and Trusov (2011) use a search engine advertising dataset from the ringtone industry over 20 days in 2007.

5. Technically, conversation data were obtained from individual users’ own Facebook page whose posts or sharing related to the apparel brand, while responsiveness data were obtained from the apparel brand’s Facebook brand page. Thus, each data point was used for a single element.

Disclosure statement

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References


