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WHAT MESSAGES TO POST? EVALUATING THE EFFECTIVENESS OF SOCIAL MEDIA COMMUNICATIONS BASED ON MARKET AND OFFERING CHARACTERISTICS

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A Dissertation Presented

By

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DEDICATION

To all my near and dear ones.

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ABSTRACT

WHAT MESSAGES TO POST? EVALUATING THE EFFECTIVENESS OF SOCIAL MEDIA COMMUNICATIONS BASED ON MARKET AND OFFERING CHARACTERISTICS

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Marketers are struggling with the successful implementation of social media executions in their marketing efforts. The effectiveness of their social media campaigns may be realized when their customers transmit company brand messages across their unique networks of friends and associates (Berger and Milkman 2012). Indeed, marketers using social media try to determine what messages will engage their customers.

In essay one, we provide guidance to B2B (business-to-business) managers by examining the usage and effectiveness of social media message strategies. Building on B2B advertising, organizational buying, and word-of-mouth theories, we highlight key differences in B2B and business-to-consumer (B2C) social media message strategies in terms of branding, message appeals, selling, and information search. Analyzing 1,467 Facebook wall posts by Fortune-500 companies, using Bayesian Models, we find differences in the usage and effectiveness (message likes and comments) of social media. Specifically, the results indicate that the use of 1) corporate brands, 2) functional and

emotional appeals, and 3) information search results in a higher percentage of message likes in B2B messages than in B2C messages. In addition, we find that B2B buyers, when compared to B2C consumers, demonstrate a higher message liking rate, but a lower message commenting rate.

In essay two, we examine how and when social media communications get transmitted by estimating a Multivariate Multilevel Poisson Model. To answer how, we focus on the two primary modes of transmission, message likes and comments. To answer when, we examine the effect of offering characteristics, products (goods) versus services on the social transmission of content. Drawing upon the same Fortune-500 dataset, we investigate the effectiveness of social media message strategies in terms of branding, message appeals, and vividness. We find that the use of corporate brand names is more effective (in terms of likes and comments) for service messages, whereas the use of images, videos, and product brand names is more effective for product messages. Furthermore, the results indicate that the use of corporate brand names, images, and videos yields a lower commenting rate, whereas the use of emotional appeals results in a higher liking and commenting rate.

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CHAPTER 1

INTRODUCTION

1.1 What is Social Media?

Social media is a form of media "[that] describes a variety of new sources of online information that are created, initiated, circulated and used by consumers [buyers] intent on educating each other about products, brands, services, personalities, and issues," (Blackshaw and Nazzaro 2004, p. 2). It is also characterized as a group of Internet-based applications that allows for the creation and exchange of user generated content (Kaplan and Haenlein 2010). According to Mangold and Faulds (2009) social media comprises a wide range of online tools including chat rooms, blogs, company sponsored discussion boards, service/products ratings websites, community forums, and social networking sites, to name a few. Social media is also described as media that allow users to build and maintain networks of friends and associates for social and professional interactions (Trusov, Bucklin, and Pauwels 2009). In sum, social media is a relatively new form of media that fosters connection in environments where customers can interact with sellers and other customers, and can access information and content through a myriad of electronic devices.

1.2 Brief Overview of Social Media

The growth of social media has been remarkable. It is estimated that about 20% of the world's population regularly uses social media and over 55% of users follow brands on sites like Facebook, Google+, Twitter, and Pinterest (Van Bellenghem, Thijis, and De Ruyck 2012). It is forecasted that by 2017, the number of social media users will total

2.55 billion, accounting for 33% of the world's population (Emarketer 2013). People throughout the world now spend over 121 billion minutes per month on social media sites like Facebook, LinkedIn, YouTube, Wikipedia, Twitter and blogs (Neilsenwire 2012). One study found that 27% of the time spent online is on social networking sites (Experian 2013).

The range of social media sites is vast and growing rapidly (Smith, Fischer, and Yongijan 2012). Facebook itself has over 1.15 billion registered users; this suggests that one seventh of the world's population uses Facebook (Facebook 2013). LinkedIn has over 238 million users including executives from each Fortune-500 company (LinkedIn 2013). Wikipedia has over 4 million articles and attracts 470 million visitors every month. It is one of the largest reference websites, with over 17.5 million users (Wikipedia 2013). Twitter has over 200 million active users who tweet over 400 million tweets everyday (Twitter 2013). On YouTube, an average of 6 billion hours of videos is watched every month and hundreds of thousands of videos are uploaded daily (YouTube 2013). Corporate blogs are akin to corporate personal webpages that can be customized to distribute information ranging from personal to technical topics (Kaplan and Haenlein 2010). By 2014, readership of blogs may increase to around 150 million Americans, or 60% of the Internet population in the US (Emarketer 2010c).

To take advantage of these phenomena, marketers have started to substantially invest in social media so they can more readily interact with their existing, prospective, and former customers. In the next five years, the social media spending budget of businesses is expected to increase by as much as 20% (Moorman 2012). It is estimated that by 2017 worldwide corporate spending on social networking sites such as Facebook, Twitter, Google+, LinkedIn, and Pinterest will reach about $11 billion (BIA/Kelsey 2013). Furthermore, about 70% of Fortune-500 companies use social media in their marketing efforts (Barnes, Lescault, and Wright 2013).

Marketers use social media to interact with their customers, increase sales, generate leads, build relationships, increase brand awareness and loyalty, and even expedite purchase decisions (Emarketer 2010a; Rapp, Beitelspacher, Grewal, Hughes 2013). They create brand communities on social media sites to share brand content with their followers who can then interact with it by liking, sharing, tweeting, and/or commenting on it (de Vries, Gensler, Leeflang 2012). The act of customers/followers sharing company content with their networks of friends is analogous to online word-of-mouth (WOM) behavior. Online WOM is important for marketers as research suggests a causal impact of WOM on sales, brand measures, stock price, and product adoption (Zhu and Zhang 2010; Chevalier and Mayzlin 2006; Godes and Mayzlin 2009; Liu 2006; Trusov, Buclin, and Pauwels 2009; Kumar and Mirchandani 2012; Rapp et al. 2013; Luo 2007). Thus, it is important for marketers to understand when and how members of their brand communities transmit content to their networks of associates and friends.

In the marketing literature, less attention has been paid to understanding the message strategies that actually influence online WOM in the social media arena (de Vries, Gensler, Leeflang 2012). In particular, research has overlooked key moderators like market characteristics (i.e., business or consumer) and offering type (i.e., products (goods) or service) and their role in formulating effective social media message strategies (Berger and Milkman 2012; de Vries, Gensler, Leeflang 2012). Furthermore, prior research on how users interact with these new electronic forms of communications (e.g., social plugins) that spread WOM in social media environments is scant (de Vries, Gensler, Leeflang 2012). “[In the social media context,] research is needed to understand how different consumer groups respond to different communications activities for different categories and markets,” (MSI 2012, p. 7). Indeed, in the past few years there have been several calls to study social media in depth (e.g., Lindgreen, Dobele, and Vanhamme 2013; Libai, Bolton, Bügel, Ruyter, Götz, Risselada, and Stephen 2010; Kozinets, de Valck, Wojnicki, and Wilner 2010; Schulze, Schöler, and Skiera 2014).

This dissertation addresses an important gap in the social media literature by: 1) investigating the moderating role of market characteristics (B2B and B2C) and offering type (products and service) on the execution of social media message strategies, and 2) exploring the similarities and differences between the two modes of social media message transmission that users use most frequently, message likes and comments.

1.3 Dissertation Contributions

The motivation for this dissertation is to address calls to investigate social media phenomena in greater depth (Rapp et al. 2013; Lindgreen, Dobele, and Vanhamme 2013; Libai et al. 2010; Michaelidou, Siamagka, and Christodoulides 2011; Schulze, Schöler, and Skiera 2014). Essay one addresses the relevant differences that exist between the B2B and B2C environments with respect to social media messages based on B2B advertising, organizational buying, and WOM theories. Furthermore, based on these differences, we test the effectiveness of social media messages using Facebook’s social plugins, likes and comments. Essay one contributes to the B2B advertising, organizational buying, and WOM literatures primarily by providing explanations and support for differences in social media message practices in business and consumer markets. Furthermore, this research deepens our understanding of the message strategies that actually influence online WOM popularity and effectiveness (de Vries, Gensler, and Leeflang 2012; Berger and Milkman 2012; Berger 2013) in the B2B social media arena. In addition, essay one describes a technique for observing and analyzing online WOM behaviors that offers important advantages over the more commonly used survey-based approach (Godes and Mayzlin 2009; Hofacker 2012).

Essay two deepens our understanding of message strategies that are likely to influence various modes of social transmission and subsequently spread WOM throughout customer networks. In essay two, we focus on how the key moderator of products versus service influences various message strategies, thus contributing to WOM, service advertising, and social media literatures. In addition, we fully explore the two modes of social transmission that users commonly use in social media environments by introducing and estimating a Multivariate Multilevel Poisson Regression Model.

Given that 70% of Fortune-500 companies actively use Facebook (Barnes, Lescault, and Wright 2013), our data sample frame enables insights and generalizability of effective WOM communications for top global brands and large businesses. This effort provides noteworthy and directly applicable implications for managers, particularly social media marketers, to improve their social media communication effectiveness. The results of this research highlight effective marketing strategies that marketers should adopt when disseminating social media communications based on market type and offering characteristics. Furthermore, the results suggest the conditions that lead customers to like or make comments on social media messages.

1.4 Dissertation Structure

This dissertation follows a two essay format. Chapter two details essay one, "What Messages to Post? Evaluating the Effectiveness of Social Media Communications in Business-to-Business and Business-to-Consumer Contexts." It highlights the differences in B2B and B2C social media communication practices. In this essay we test current B2B marketing practices (study 1) and their effectiveness (study 2) by measuring message likes and comments. Chapter three is comprised of essay two, "Assessing the Levels of Social Media Message Effectiveness for Services and Products." In this essay we test the effective communication strategies for products and services.

In chapter 4, we discuss the contributions from across the two essays, directions for future research, and research limitations. In particular, we highlight the message strategies that marketers are likely to find most effective when communicating with buyers versus consumers or when promoting products versus services. Our results also reflect the strategies that marketers could use to influence particular mode of diffusion among the followers of brand communities and their unique networks of friends and associates.

CHAPTER 2

WHAT MESSAGES TO POST? EVALUATING THE EFFECTIVENESS OF SOCIAL MEDIA COMMUNICATIONS IN BUSINESS-TO-BUSINESS AND BUSINESS-TO-CONSUMER CONTEXTS

2.1 Introduction

Business-to-business (B2B) marketers have long used traditional marketing communication tactics to promote their brands. These include tradeshows, newsletters, trade publications, technical product sheets, company brochures, company websites and various other mediums. Personal selling is considered to be particularly effective. More recently, B2B marketers have begun to utilize mass media-oriented strategies once used virtually exclusively by their business-to-consumer (B2C) counterparts, and shifted their emphasis from traditional media like print advertising to more typical consumer media including television advertising, infomercials, social media, and endorsements (e.g., Gilliland and Johnston 1997; Mudambi 2002; Michaelidou, Siamagka, and Christodoulides 2011; Wiersema 2013). With this trend, many B2B companies have now started diverting their marketing efforts and resources to a new consumer advertising medium – online advertising. Online advertising is perceived to be more efficient and suggests a greater return on marketing investments. A study by Forrester shows that B2B interactive spending (e.g., online advertising) will double to $4.8 billion by 2014 (Greene 2010). Of all the online advertising mediums, social media is getting the utmost attention. In a survey of top U.S. Marketers, Moorman (2012) found that, B2B marketers currently allocate about 7.6% of their marketing budgets to social media and it is projected to increase to 18.8% in the next five years. Fortune-500 companies like Accenture, Cisco, Caterpillar, Avaya, DuPont and IBM have dedicated significant dollar amounts and resources towards social media, and around 70% of Fortune-500 companies have a strong presence on sites such as Facebook, Twitter, and YouTube (Barnes, Lescault, and Wright 2013).

The growth of social media as a part of the B2B marketing mix looks promising. Various polls have suggested that pilot use of social media is on the rise and B2B marketers (e.g., American Express, Siemens and Indium) are increasing their use of social media. According to a study by BtoB Magazine, 93% of B2B marketers use some form of social media to engage with their customers (Holden-Bache 2011). This is not surprising as marketers believe that social media can help build brand awareness, enhance brand reputation and generate sales leads (Emarketer 2010a). B2B marketers are also using social media to interact with buyers due to the importance of relationships in organizational buying. Organizational buyers recognize the value of social media as a new source of information and have begun to use social media in their purchasing decisions (Ramos 2008; Burris 2010). Besides, buyers expect their suppliers to actively interact and engage with them on social media sites (Gillin and Schwartzman 2011; Michaelidou, Siamagka, and Christodoulides 2011; Rapp et al. 2013).

Despite the move to social media, B2B marketers are struggling with the successful implementation of social media (Michaelidou, Siamagka, and Christodoulides 2011). For example, a survey of B2B marketers using social media revealed that only 11% found it to be highly effective for generating leads (Paul 2012). Another survey found that 37% of marketers did not know enough about social media to know when, where, and how to implement it in their marketing efforts (Emarketer 2010b).

Furthermore, Michaelidou, Siamagka, and Christodoulides (2011) found that 44% of small B2B businesses were not using social media in their marketing communication efforts due to an uncertainty concerning how it would support their brands; 47% reported that they were unfamiliar with social media or lacked the skills necessary to implement it.

Given this lack of guidance, B2B marketers are likely to follow the lead of their counterpart, B2C (Michaelidou, Siamagka, and Christodoulides 2011; Rapp et al. 2013). Yet, prior research suggests that the two contexts differ enough in their marketing strategies to justify a dedicated study of social media phenomena in the B2B context. Such efforts would be consistent with calls to and research priorities set to study social media in increased depth (MSI 2012; Michaelidou, Siamagka, and Christodoulides 2011; Wiersema 2013). With the rise of and significant investment in social media, it is worthwhile for academics to explore and better understand the implementation of social media in the B2B arena. Specifically, what social media communication strategies should B2B marketers implement?

The objective of this research is to highlight the relevant differences that exist between the B2B and B2C contexts as they impact social media message creation. In so doing we draw on word-of-mouth (WOM), B2B advertising and organizational buying theories. We test the effectiveness of social media messages in the two contexts using Facebook's social plugins "Likes" and "Comments." The data used in this essay are comprised of Fortune-500 Facebook wall posts collected over a week. This study contributes to the WOM, B2B advertising and organizational buying literatures primarily by providing explanations and support for the differences in social media message practices for B2B and B2C contexts. Furthermore, this research deepens our understanding of the message strategies that actually influence online WOM popularity and effectiveness (de Vries, Gensler, and Leeflang 2012; Berger and Milkman 2012) in the social media arena. The results have direct applicable managerial implications for B2B managers. In study 1 we test current social media marketing practices across B2B and B2C marketers and in study 2 we test the effectiveness of these strategies through number of likes and comments. We find that there are differences in the practices and effectiveness of social media strategies in terms of branding, message appeals, selling and information dissemination approaches. Furthermore, we find that propensities for liking and commenting on messages are different across B2B buyers and B2C consumers. Buyers are less likely to comment on messages than consumers, for example.

Essay one is organized as follows: we (1) provide our research contributions, (2) explain the flow and process of communication in a social media context to present our theoretical framework using WOM and communication theories, (3) highlight relevant differences between B2B and B2C based on organizational buying and B2B advertising theories, and state our hypotheses, (4) test our hypotheses through study 1 (use of B2B social media communication strategies) and study 2 (effectiveness of B2B social media communication strategies), (5) provide discussion followed by managerial implications, and (6) list study limitations followed by directions for future research.

2.2 Contributions of the Current Research

This research makes several noteworthy contributions to the B2B social media literature. First, building on the traditional communication model (Shannon and Weaver 1949; Duncan and Moriarity 1998), it offers a theoretical explanation for communication flow in social media (Yadav and Pavlou 2014). Unlike traditional communication models, our social media communication model incorporates the role of networks of friends and addresses how customers process and respond to the social media messages sent out by marketers. Furthermore, we use WOM theories (psychological motivations) to argue that motivations need to be made salient for customers to share content with their networks of friends and associates (Lovett, Peres, and Shachar 2013). Overall, this theoretical framework helps us better understand the social media communication flow between marketers and customers.

Second, we argue that motivations to share messages will be more salient for B2B buyers than B2C consumers based on message characteristics. In the process, we highlight the differences between B2B and B2C message strategies and test conditions for effective B2B strategies. To our best knowledge this is the first study to evaluate effective social media B2B communication strategies for branding, message appeals, selling, and information search purposes. Our data, comprised of Fortune-500 Facebook wall posts, are novel and rich enough to test the usage and effectiveness of the message strategies implemented by B2B marketers. Thus, this research contributes to the organizational buying, B2B advertising and WOM literatures by identifying and testing usage and effectiveness of B2B social media practices.

Third, we make a contribution by testing the effectiveness of social media messages by measuring the number of likes and comments. These two outcomes measures have not been simultaneously examined before in this context. We argue that liking and commenting are different WOM behaviors and further argue that the commenting behavior is likely to vary across B2B buyers and B2C consumers. Given that B2B buying process is unique and different from B2C buying (Brown, Zablah, Bellenger, and Donthu 2011a) we find differences in commenting and liking for the two contexts. This furthers our understanding of WOM behaviors on social media for the two domains, B2B and B2C.

Finally, our results have direct applicable implications for managers. Our results will provide guidance to managers who are responsible for their social media communications. Specifically, based on our findings, managers can implement appropriate branding, message appeals, selling and information search strategies to improve engagement among their buyers and networks.

2.3 Social Media Communication Model

Marketers create brand communities in the form of "pages" on social media sites via which they share marketing communications with their customers. Marketers, when communicating on social media site, have to decide which strategies to implement in terms of branding, message appeals, selling, and the dissemination of information. Due to lack of guidance, B2B marketers are challenged to select the right approach and are mostly likely to use communication strategies implemented in traditional outlets or follow the lead of their B2C counterparts. It is crucial for B2B marketers to use appropriate strategies to motivate their customers to share the brand communications, given that engaging with social media brand messages has proven to influence brand outcomes (e.g. brand awareness, brand loyalty) as well as financial outcomes (e.g. sales, ROI, and profits) (Rapp et al. 2013; Kumar and Mirchandani 2012). To understand the decision process of B2B marketers and how it motivates customers to engage with the brand messages we draw from the communication and WOM theories to understand communication flows in social media, primarily between marketers and customers and their networks of friends and associates.

Communication is a human activity that links people and businesses together and creates relationships (Duncan and Moriarity 1998). The traditional communication model (Shannon and Weaver 1949) suggests that a sender (source) encodes or creates a desired message which is transmitted through a channel (medium) and the receiver decodes or processes the message. In an interactive medium, such as that of the social media environment, the sender and the receiver interchange positions as they interact with each other's messages (Labrecque, Zanjani, and Milne 2011; Dennis, Fuller, and Valacich 2008). This is a feedback loop that sends a receiver's response back to the sender.

In Figure 2.1, we adapt the Shannon and Weaver (1949) communication model to the social media context, highlighting the communication flows between marketers and B2B buyers/B2C consumers and their networks of friends (Yadav and Pavlou 2014). Here the source is the marketer, the medium is social media, the receiver is the intended audience, and the feedback is the flow of communication that is primarily between target audiences and their networks of friends. Marketers encode appropriate messages and send them out to their B2B and B2C target audiences. These buyers and consumers receive and decode the messages. This decoding process involves information processing where the receivers of the message elaborate on a message to understand it, integrate it into their cognitive schema, and possibly take appropriate actions (Dennis, Fuller, and Valacich 2008). It is at the decoding stage where buyers and consumers are likely to be motivated to share the message based on the message's characteristics. Buyers and consumers, when motivated, are likely to encode (by commenting, liking, or sharing) the message and the intended receivers of this message are primarily their networks of friends and associates. The networks of friends receiving the message will decode the shared message and likely encode it. For marketers, it is important to encourage the encoding of messages by customers and their networks of friends as this encoding process is analogous to WOM behaviors that help spread their brand messages. Indeed, marketers have to select appropriate brand strategies to motivate their audiences to spread their brand messages.

2.3.1 Psychological Motivations

The WOM literature highlights several key psychological motivations that are likely to influence individuals to transmit content (Lovett, Peres, and Shachar 2013; Berger and Milkman 2012; Hennig-Thurau, Gwinner, Walsh, and Gremler 2004). These include the need to share information, express self-identity, uniqueness and expertise, increase self-worth among friends, concern for others, express feelings, emotions, and excitement, economic incentives, and derive social benefits. Marketers can activate some of these psychological motivations through implementation of appropriate brand strategies (motivations to express self-identity and uniqueness), message appeals (motivations to express feelings, emotions, and excitement and need to share information), selling strategies (motivations such as economic benefits and increase self-worth among friends), and informational strategy (motivations such as need to share information, express expertise, and derive social benefits) in their social media communications (de Angelis, Bonezzi, Peluso, Rucker, and Costabile 2012; Lovett, Peres, and Shachar 2013; Alexandrov, Lilly, and Babakus 2013).

The objective of marketers is to facilitate engagement with their brand messages among their customers and their networks of friends (encoding of messages by customers and their networks of friends). For the desired message encoding to succeed, the customers and their networks of friends should be motivated to spread the message (decoding of messages by customers and their networks of friends). Thus, marketers have to use appropriate communication strategies to motivate their customers and their networks of friends to share content. We argue that some of these psychological motivations are likely to be activated by the appropriate message strategies used by marketers when communicating to buyers versus consumers. Specifically, marketers have to match their message strategies with the underlying psychological motivations to spread WOM of brands when communicating with buyers versus consumers.

We suggest that B2B and B2C marketers use different encoding processes (message strategies) when persuading and motivating buyers versus consumers. In addition, the choice of the appropriate message strategy depends on how buyers and consumers are likely to decode (saliency of psychological motivations) and encode (WOM) the messages. We suggest that buyers and consumers will use different decoding and encoding processes. Specifically, we argue that some motivations will be more salient for buyers than consumers.

2.3.2 B2B versus B2C Social Media Communication Strategies

Scholars have documented the unique characteristics of the B2B context relative to the B2C context (Mudambi, Doyle, and Wong 1997; Zablah, Brown, and Donthu 2010). Broadly speaking, these differences exist because of their decision-making processes and product offering characteristics (Brown, Zablah, Bellenger, and Johnston

2011b). B2B product offerings have a tendency to be more technical and functional, and B2B buyers therefore utilize a more formal and generally longer, group buying process. Moreover, buyers tend to perceive higher levels of performance and economic risk, and subsequently are much more involved in the purchasing decision. To mitigate such risks, both buyers and sellers seek to establish long-term, collaborative relationships, unlike typical end-consumers (Homburg, Klarmann, and Schmitt 2010; Zablah, Brown, and Donthu 2010; Lynch and de Chernatony 2004).

Because of these characteristics, B2B marketers use different encoding processes and thus generally pursue different branding and marketing communication strategies (Brown et al. 2011b). More specifically, B2B marketers tend to promote their corporate brands much more than individual product brands (Mudambi 2002), and generally make more functional appeals to their audience (Turley and Kelly 1997). In addition, the practice of commercialism (hard sell approaches) is less frequent whereas the practice of information dissemination is more frequent in B2B context.

Furthermore, buyers and consumers are likely to use different decoding and encoding processes. Lothia, Donthu, and Hershberger (2003) note that in B2B environments viewers of online advertisements process information differently than viewers in B2C environments thus affecting their decoding process and subsequently their encoding process. B2B buyers tend to be highly involved and rational and are likely to use high levels of cognition during their purchase decision process, whereas B2C consumers tend to be less involved and use low levels of cognition; plus, consumers demonstrate impulsive buying behavior when purchasing some offerings. Lothia, Donthu, and Hershberger (2003) indicate that B2B online advertisements should be more cognitive in nature because their generally high-involvement situations require buyers to use central routes of processing. On the other hand, B2C advertisements should be more affective in nature because their generally low-involvement situations allow consumers to use peripheral routes of persuasion. Furthermore, B2B buyers tend to elaborate more on corporate branding and are more likely to search for information due to higher associated risks in the decision process (Brown et al. 2011a; Gilliland and Johnston 1997). In addition, buyers are hesitant to make impulse purchase decisions (Brown et al. 2011b).

Based on the previous discussion, we categorize social media message strategies according to four criteria that marketers are likely to implement: brand strategy approach, message appeals, selling strategy approach, and information search. We use this classification to outline the differences in the encoding process between B2B and B2C marketers as well as the encoding process across buyers and consumers and their networks of friends. We expect to see the use of corporate brand names, functional appeals, and links or cues for information search more frequently in B2B social media executions. Accordingly, we anticipate that the use of product brand names, emotional appeals, and direct calls to purchase will be less frequent in B2B social media executions. We test these differences in study 1. B2B buyers use different decoding and encoding process, we expect that messages containing corporate brand names, functional appeals, and links or cues for information search are more effective in B2B social media communications. Accordingly, we anticipate that the use of product brand names, emotional appeals, and direct calls to purchase will be less effective in B2B social media executions. We test the effectiveness of social media communications in study 2.

2.4 Effectiveness of Social Media Messages

When motivated to share a message, buyers and consumers have several options to encode (e.g., liking and/or commenting) the message and subsequently share the message with their networks of friends. Indeed, social media sites provide users with several modes to transmit content to their networks of friends. In this research we focus on two sharing behaviors, liking messages and commenting on messages. Users use these tools ubiquitously.

Buyers and consumers once motivated to share a message need to decide how to share the message, by liking and/or commenting. We argue that the decision to like or comment on a message can be explained by the dual process theory (Kahnemann 2011). That is, individuals in the system 1 process are more likely to like a message whereas those in the system 2 process are more likely to comment on a message. Liking a message is intuitive, reflexive, and less of a cognitive process, and is therefore in line with the system 1 process (Kahnemann 2011; Evans 2008) whereas commenting on a message is slow, reflective, and more of a cognitive process, and is therefore in line with the system 2 process. Furthermore, compared to liking, commenting is a deeper form of engagement as users can share their opinions.

Based on the previous discussion we argue that liking and commenting on a message are different forms of WOM behaviors. We anticipate observing some differences across liking and commenting of B2B and B2C social media messages for various message strategies. Specifically, as buyers are more involved and busy in their buying process they are less likely to be in the system 2 process of encoding as it is time consuming and requires more cognition and resources. Indeed commenting on a message not only requires decoding the original message sent out my marketers but also decoding the chain of previous comments to encode an appropriate response. Thus, the commenting process can become very time consuming and cognitively overwhelming. Given the unique nature of B2B buying process, buyers will be less likely to comment on social media messages as this would divert their vital resources (time and cognitive ability) in their purchase decisions. For B2C consumers we expect to see more comments given they have more time and resources than B2B buyers to share their opinions with their networks of friends.

Although we test the effectiveness of social media messages in terms of number of message likes and comments, we develop our hypotheses only for message likes. Liking a message can be derived directly from the message strategies implemented by the marketers. However, comments cannot be directly derived from message strategies as they are severely influenced by the previous message comments (de Vries, Gensler, Leeflang 2012). Our focus in this research is to study the effectiveness of message strategies sent out by the marketers. Given that message comments are heavily influenced by previous comments, we state our effective social media hypotheses for message likes and simply explore message comments in our analysis. Indeed, liking and commenting can both influence each other so we explore these two measures of effectiveness simultaneously.

Analyzing the effectiveness of social media messages across likes and comments will provide guidance to managers who aim to increase the number of likes and/or number of comments pertaining to their messages. Specifically, managers can use this information to tailor their marketing strategies based on customer input. Liking messages would provide information on what type of content consumers like to share with their friends whereas commenting will provide rich information on customers' opinions of products and services. Thus, marketers can assess customer insights by listening to their opinions through comments.

2.5 Hypotheses

Based on a review of the literature, we examine the overall empirical model shown in Figure 2.2 in two studies. The following is the rationale for each of the hypotheses we test.

2.5.1 Brand Strategy Approach

Scholars have noted the importance of B2B branding (Shipley and Howard 1993; Mudambi 2002; Kim, Reid, Plank, and Dahlstrom 1998), and there is a growing stream of research that focuses on the role of corporate branding (e.g. Keller and Aaker 1998, Brown 1998, Brown and Dacin 1997) and its importance in organizational buying in particular. Researchers have noted that B2B brands communicate both tangible attributes (e.g., product performance) and intangible attributes (e.g., reputation, distribution and support services) (Brown et al. 2011b; Michaelidou, Siamagka, and Christodoulides 2011). Thus, B2B marketers focus more on corporate name branding (e.g., Caterpillar, Cisco, IBM, DuPont and Intel), rather than product name branding (e.g., Crest, Downy, Dove, Maggie and Snickers), and usually follow an umbrella branding approach -- all products tend to be named after the corporate brand name (Michell, King, and Reast 2001; Shipley and Howard 1993). Thus, B2B marketers are likely to use different branding strategies when encoding a message compared to B2C marketers. We expect B2B marketers use more corporate brand names in their social media communications to buyers, whereas B2C marketers use more product brand names in their social media communications to their consumers.

> H1: Corporate brand names are used more frequently in B2B social media messages than in B2C social media messages.
>
> H2: Product brand names are used more frequently in B2C social media messages than in B2B social media messages.

Buyers seek to express their unique identity, self-enhancement, and attachment with brands by sharing brand messages. These motivations are likely to be more salient when buyers decode corporate brand names in messages. When buyers receive a message containing corporate brand names, they are likely to elaborate more and subsequently are motivated to encode the message by liking it. This effect is more likely to be pronounced for B2C consumers when the message contains product names. Consumers are more likely to react to a message when they see product brand names in the messages as they seek to express their unique identity, self-enhancement, and attachment with product brand names. As such, consumers are more likely to like messages containing product brand names thus improving the effectiveness of the message.

> H3: The use of corporate brand names will have a higher percentage of message likes in B2B social media messages than in B2C social media messages.
>
> H4: The use of product brand names will have a higher percentage of message likes in B2C social media messages than in B2B social media messages.

2.5.2 Message Appeals

The most basic element of advertising message development is the decision to use either a functional/rational appeal or an emotional appeal (e.g., Turley and Kelly 1997; Lothia, Donthu, and Hershberger 2003). Emotional appeals refer to themes such as fear, humor, romance, sensuousness, adventure, guilt, play/contest, and other emotional cues (Turley and Kelly 1997). Functional appeals refer to specific product specifications, features, performance, quality, economic indicators, convenience, ease of use, profitability and other more tangible cues.

Functional/rational appeals in B2B social media messages are likely to be most effective because the buying process of complex offerings involves assessing information to make a sound purchase. Regardless of the purchase situation, organizational buying behavior often involves extensive problem solving (Brown et al. 2011a). Research suggests that extensive problem solving involves a more cognitive decision-making process (Jensen and Jepsen 2007) and that high involvement purchases are complex -- a typical characteristic in business markets (Schiffman and Kanuk 2004). Thus, functional appeals are likely to be particularly important in B2B social media messaging.

Lothia, Donthu, and Hershberger (2003) found that emotional appeals were more effective in B2C online banner ads than in B2B online banner ads. This is not surprising, as emotional appeals tend to be effective in consumer marketing (Goldberg and Gorn 1987) due to the more value-expressive nature of B2C offerings (Bruzzone 1981). Furthermore, scholars have emphasized that message appeals should match the offering type (Shavitt 1990; Johar and Sirgy 1992). A more emotional appeal should be used for a value-expressive offering and a more functional appeal for a utilitarian offering (Vaughan 1980). Thus, B2B marketers are likely to use different message appeals when encoding a message compared to B2C marketers. We expect B2B marketers use more functional/rational appeals in their social media communications to buyers whereas B2C marketers use more emotional appeals in their social media communications to their consumers.

> H5: Functional/rational appeals are used more frequently in B2B social media messages than in B2C social media messages.
>
> H6: Emotional appeals are used more frequently in B2C social media messages than in B2B social media messages.

Buyers seek to express their expertise, concern for other buyers, and need to share information by sharing brand messages with functional appeals. These motivations are likely to be more salient when buyers decode functional appeals in messages. Buyers are more likely to elaborate on messages containing functional appeals due to complex and extensive group buying processes and subsequently are motivated to encode the message by liking it, thus improving the effectiveness of the message. Consumers seek to express their feelings, emotions and excitement by sharing brand messages with emotional appeals. These motivations are likely to be more salient when consumers decode emotional appeals in messages. Consumers are more likely to elaborate on messages containing emotional appeals due to more expressive products and impulse buying behaviors. Subsequently, consumers are likely to be motivated to encode such messages by liking it.

> H7: The use of functional/rational appeals will have a higher percentage of message likes in B2B social media messages than in B2C social media messages.
>
> H8: The use of emotional appeals will have a higher percentage of message likes in B2C social media messages than in B2B social media messages.

2.5.3 Selling Strategy Approach

Direct calls to purchase (or so-called "hard sell" approaches) refer to explicit commercialism encouraging prospective customers to make an immediate purchase. When B2B buyers perceive that a company uses its social media site for hard sell commercialism, their interest in the site is likely to diminish to the point that they may never return (Spekman and Dotson 2009). This is because of the longer buying cycles and the rigor involved in the processing of complex information that buyers seek when making purchase decisions. Thus, organizational buyers tend to be reluctant to respond to direct calls to purchase.

On the other hand B2C consumers are more likely to respond positively to commercialism on corporate social media sites. In B2C contexts the emphasis is on selling and encouraging a more impulsive, short-term sale, rather than the development of a long-term relationship. Thus, companies like Wal-Mart, Gap, KFC, and others find success with messages that use hard sell approaches (e.g. apply now, buy-one-get-one-free, sale, and shop today) as these messages very well may entice B2C consumers to make an immediate purchase. Thus, B2B marketers are likely to use a different selling strategies when encoding a message compared to B2C marketers. We expect B2B marketers to use hard sell approaches infrequently in their social media communications whereas we expect B2C marketers to use hard sell approaches more frequently in their social media communications.

> H9: The use of direct calls to purchase is more frequent in B2C social media messages than in B2B social media messages.

Consumers seek to enhance their self-worth among friends, and derive social and economic benefits by sharing brand messages with direct calls to purchase. These motivations are likely to be more salient when consumers decode direct calls to purchase in messages. B2B buyers are less likely to elaborate on messages using hard sell approaches as their buying cycle is usually longer, they perceive greater purchase risk, and they are less likely to be impulsive compared to B2C consumers. Subsequently, buyers are less likely to be motivated to encode messages favorably using direct calls to purchase. B2C consumers, on the other hand, are more likely to elaborate on messages containing cues for direct purchases due to more impulsive buying behavior and less complex decision making. Subsequently, consumers are likely to be motivated to encode such messages by liking it.

> H10: The use of direct calls to purchase will have a higher percentage of message likes in B2C social media messages than in B2B social media messages.

2.5.4 Information Search

Organizational buyers tend to be experts in their respective fields and thus engage in more analytics during the purchasing process to justify their purchase decisions (Gilliland and Johnston 1997). As such, buyers view technical information on products and/or services from the manufacturer as an important part of the buying process (Mudambi, Doyle, and Wong 1997). B2B marketers tend to provide relevant information through various sources that prospective buyers can use to make an informed buying decision. The Internet provides an efficient channel for acquiring information to make buying decisions for both buyers and consumers (Turley and Kelly 1997). B2B buyers have started to realize the importance of the Internet, and particularly social media, as a new source of information (Ramos 2008; Burris 2010; Rapp et al. 2013).

Messages sent through social media sites provide the capability to post website links which generally lead to a host of informational resources (e.g. white papers, research reports, press releases, detailed technical specifications, informational videos, or partner sites). Embedded links in a message can be used to provide buyers with more information about the offering and/or the company. Besides, B2B marketers are also likely to use cues in messages that would entice buyers to look for information (e.g. more information, read more, click here, and read on). As B2B buying processes are more rational, information search tends to be more extensive in B2B settings compared with in B2C settings. Thus, B2B marketers are likely to use different message strategies when encoding a message compared to B2C marketers. We expect B2B marketers to use cues and links for information search more frequently in their social media communications to buyers.

> H11: The use of embedded links and cues for additional information search is more frequent in B2B social media messages than in B2C social media messages.

Buyers seek to express their need to share information, increase their self-worth, and derive social benefits, and express their expertise by sharing brand messages containing cues and links for information search. These motivations are likely to be more salient when buyers decode messages containing cues and links for information search. B2B buyers tend to undergo extensive research in order to make a sound purchase decision. As such, buyers are more likely to elaborate on messages containing cues and links for information search. Thus, buyers are likely to be motivated to encode the informational message by liking it. Consumers, on the other hand, are less likely to be motivated to elaborate on messages containing links and cues for information search due to more impulsive buying behavior and less complex decision making. Subsequently, consumers are less likely to encode such messages favorably.

> H12: The use of embedded links and cues for additional information search will have a higher percentage of message likes in B2B social media messages than in B2C social media messages.

The summary of which hypotheses will tested in the two studies is shown in Table 2.1. Next, we describe study 1.

2.6 Study 1

In study 1 we explore the differences in the encoding process used by B2B and B2C marketers when disseminating social media messages (Refer to Table 2.1). This study investigates the current social media message strategies between these types of marketers.

2.6.1 Method

2.6.1.1 Data

Given the breadth of social media sites and their widespread usage, we examine Facebook, the largest and the most popular social media site (Neilsenwire 2012). Our data are drawn from 280 Fortune-500 companies' Facebook wall posts. The list of Fortune-500 companies with Facebook accounts was based on Barnes (2010). Given that some companies have multiple Facebook accounts, we followed 303 accounts. They were tracked the week of 9/29/11. This resulted in 1,498 unique company wall posts from 214

Facebook accounts that were active during this time period. Refer to Appendix A for the list of Fortune-500 companies.

2.6.1.2 Content Analysis

Two research assistant coders were used to code the messages. The coders went through four training sessions over a period of two weeks to ensure that they understood the key concepts and became efficient in the coding scheme (Refer to Appendix B for the coding scheme). Both coders coded over 60 messages during the training sessions. The intercoder reliability between the two coders was calculated on a randomly selected subsample of 100 messages from a separate data set (Lothia, Donthu, and Hershberger 2003; Neuendorf 2002). The intercoder reliability was calculated for the independent variables (message characteristics) as well as the communication type (intended audience -- B2B, B2C or both) using Rust and Cooil’s (1994) proportional reduction in loss index (PRL); a value of 0.70 is acceptable whereas 0.90 or above is desired. All reliabilities were high and above desired levels (mean PRL = 0.96). The high reliability assumes that the coders are fungible with virtually no individual differences contributing to their evaluations. The dataset for analysis was divided equally into two sets and each coder coded one of the two sets. Thirty-one messages were identified as both B2B and B2C messages and were eliminated from our data set leaving a total of 1,467 messages for analysis.

2.6.2 Results

2.6.2.1 Descriptive Statistics

In Table 2.2 we report the descriptive statistics of the message strategies used in B2B and B2C messages. The dataset was comprised of 22.2% B2B messages and 77.8% B2C messages. Overall, there were more B2C messages than B2B messages. As predicted, we find that the percentage use of corporate brand names (B2B = 41.4%; B2C = 27.1%), functional appeals (B2B = 23.0%; B2C = 15.6%) and embedded links and cues for additional information search (B2B = 88.7%; B2C = 78.4%) is higher in B2B messages than compared to B2C messages. On the other hand, the percentage use of product brand names (B2B = 19.6%; B2C = 26.1%), emotional appeals (B2B = 26.7%; B2C = 61.1%) and direct calls to purchase (B2B = 3.7%; B2C = 16.3%) is higher in B2C messages compared to B2B messages.

2.6.2.2 Bayesian Analysis

To test hypotheses H1, H2, H5, H6, H9, and H11, we ran a logistic regression to compare the message strategies across B2B and B2C messages using Bayesian Analysis. The reason for choosing Bayesian Analysis was to get more clarity and richer information through posterior distributions of our parameters as well as to have the ability to perform multiple comparisons of interest (Zyphur and Oswald 2013; Kruschke 2010). Furthermore, given that we have small sample sizes for some conditions, especially in the B2B context, Bayesian estimation was appropriate as it incorporates priors and data information; estimates can be computed which would be difficult with MLE methods (Zyphur and Oswald 2013; Kruschke 2010).

The priors for beta coefficients were drawn from a normal distribution with means set as zero and a low precision (0.01). The model was estimated using Gibbs sampler (MCMC) (Kruschke 2010) using 50,000 draws with a burn-in of 10,000. The Bayesian code for the model is provided in Appendix C. In Appendix D, we present the posterior distributions with the means and 95% HDIs and in Table 2.3 we report the means and standard deviations of the posterior distributions of the parameters.

H1 stated that the use of corporate brand names is more frequent in B2B messages than in B2C messages. The variable representing corporate brand name was positive and significant ($\beta = 0.67$, SD = 0.15) thus supporting H1. H2 stated that the use of product brand name is more frequent in B2C messages than in B2B messages. H2 was supported as the variable representing product brand name was negative and significant ($\beta = -0.41$, SD = 0.18). H5 stated that the use of functional appeals is more frequent in B2B messages than B2C messages. The variable representing functional appeal was positive but non-significant ($\beta = 0.33$, SD = 0.18) thus H5 was not supported. H6 stated that the use of emotional appeals is more frequent in B2C messages than in B2B messages. H6 was supported as the variable representing emotional appeal was negative and significant ($\beta = -1.27$, SD = 0.15). H9 stated that the use of direct calls to purchase is more frequent in B2C messages than in B2B messages. H9 was supported as the variable representing direct calls to purchase was negative and significant ($\beta = -1.30$, SD = 0.32). H11 stated that the use of links and cues for information search is higher in B2B messages than in B2C messages. The variable representing presence of information search in a message was positive and significant ($\beta = 0.51$, SD = 0.20) thus supporting H11.

2.6.3 Discussion

The purpose of study 1 was to test the key differences in the social media message strategies (encoding process) used by B2B and B2C marketers. We tested six hypotheses based on these differences in encoding processes across B2B and B2C marketers and we found support for five of them.

In B2B contexts, corporate name branding is more frequent whereas in B2C contexts, product name branding is more frequent. Likewise, we expect B2B marketers to highlight corporate brand names in their social media messages whereas we expect B2C marketers to highlight product brand names in their social media messages. Our results show that the percentage use of corporate brand names is higher in B2B social media messages compared with B2C messages. The percentage use of product brand names is higher in B2C social media messages compared with B2B social messages. Furthermore, we find that B2B social media messages use more corporate brand names (41.4%) than product brand names (19.6%), (Refer to Table 2.2 and Appendix D). This finding reinforces the importance of corporate branding in B2B contexts.

Perhaps our most intriguing finding is that there appears to be no difference in the use of functional appeals between the two contexts. We find that emotional appeals are used more frequently in B2C social media messages compared with in B2B social media messages. Furthermore, our data suggest that B2B social media messages use a similar number of emotional appeals (23.0%) and functional appeals (26.1%) (Refer to Table 2.2 and Appendix D). Brown et al. (2011b) suggest buyers do rely on emotional cues depending on the complexity and intangibility of the offering. The usage of emotional appeals might provide B2B brands with a differential advantage and also might facilitate customer relationships with existing customers (Lynch and de Chernatony 2004). This might explain non-significant finding for the use of functional appeals that might be more applicable and appealing to new prospects. Our results indicate that B2B marketers use social media more for relationship building than for generating leads (Rapp et al. 2013). Our results show that B2C social media messages use a higher percentage of direct calls to purchase than B2B messages. It is interesting to observe the lower percentage use of direct calls to purchase in both contexts, however. This suggests that marketers do not use social media as a selling tool. The dynamics of social media advertising suggests a distinct approach compared with more traditional advertising, one where hard sell approaches are less appropriate. Our data support the difference in how social media information is used between the two contexts. We find that B2B social media messages use a higher percentage of links and cues for information search in their messages compared with B2C social media messages. Also, our data show a higher usage of cues and links for information in B2B (88.7%) as well as B2C (78.4%) social media messages. Regardless of the context, marketers use social media as an information sharing platform.

2.7 Study 2

In study 2 we explore the differences in the encoding process between B2B buyers and B2C consumers and their networks of friends. In particular, we test which message strategies are effective for B2B compared with B2C social media messages. In addition, we further explore the effectiveness of messages: depending upon a message's characteristics, which WOM behaviors (liking and/or commenting) do B2C consumers and B2B buyers use to share messages?

2.7.1 Method

2.7.1.1 Data

The coders recorded the number of likes and number of comments for each of the 1,467 messages. These counts, number of likes and comments, for each message were used as measures of effectiveness (de Vries, Gensler, Leeflang 2012). Furthermore, the coders recorded the message time and fanbase variables. Message time is the time when the message was sent out to the time when the data was archived. Fanbase is the total number of fans (fan likes) of each Facebook (brand) account. These variables were added as control variables in our model. We expect that message time as well as fanbase will have a positive influence on number of likes and number of comments. That is, as the message time increases so does the number of message likes and comments. Also, Facebook accounts with a larger fanbase will have a larger number of message likes and comments.

2.7.2 Results

2.7.2.1 Descriptive Statistics

In Table 2.4 we report the descriptive statistics. Overall, B2C messages compared to B2B messages have a higher volume of message likes (B2B = 19, SD = 65; B2C = 621; SD = 5,515) and comments (B2B = 2, SD = 8; B2C = 78, SD = 341), as well as have a larger fanbase (B2B = 80,874, SD = 497,956; B2C = 1,700,903, SD = 3,793,071). The data show a high degree of variation across B2B and B2C messages for number of message likes and comments as well as fanbase. It is not unusual to find such a high degree of variation (de Vries, Gensler, Leeflang 2012).

2.7.2.2 Bayesian Analysis

To test our hypotheses H3, H4, H7, H8, H10, and H12, we ran a bivariate Poisson Bayesian model (Ntzoufras 2011) to compare the effectiveness of social media messages across B2B and B2C. Given a high correlation across number of likes and number of comments, running a bivariate analysis was appropriate ($r = 0.65$, $p<0.001$). The priors for beta coefficients were drawn from a normal distribution with means set at zero and a low precision (0.01). The model was estimated using Gibbs sampler (MCMC) (Kruschke 2010) using 50,000 draws with a burn-in of 10,000. The Bayesian code for the model is provided in Appendix C.

2.7.2.2.1 Main Effects Model

First, we ran the main effects model with all the message characteristics, communication type (B2B/B2C), and the control measures fanbase and message time. The control measures were transformed to natural log for fanbase and square root for message time. Furthermore, none of the correlations between exogenous variables exceed 0.29, indicating minimal issues of multicollinearity in our analysis. In Table 2.5 we report the means and standard deviations of the posterior distributions of the parameters.

The variable representing corporate brand names was negative and significant for both message likes ($\beta_{Likes} = -0.27$, SD = 0.01) and message comments ($\beta_{Comments} = -0.25$, SD = 0.01) suggesting that the use of corporate brand names reduced the effectiveness of social media messages. The use of product brand names was negative and significant for message likes ($\beta_{Likes} = -0.25$, SD = 0.01) but was positive and significant for message comments ($\beta_{Comments} = 0.20$, SD = 0.01). The use of product brand names in social media messages had a higher percentage of comments but lower percentage of likes. The variable representing functional appeals was positive and significant for message likes (β_{Likes} = 0.01, SD = 0.00) but was negative and significant for message comments ($\beta_{Comments}$ = -0.47, SD = 0.02) suggesting that the use of functional appeals increased the percentage of likes but reduced the percentage of comments for social media messages. The use of emotional appeals increased the effectiveness of social media messages. Emotional messages had a higher percentage of likes (β_{Likes} = 0.59, SD = 0.01) and comments ($\beta_{Comments}$ = 1.51, SD = 0.02). The variable representing direct calls to purchase was negative for both likes (β_{Likes} = -0.59, SD = 0.01) and comments ($\beta_{Comments}$ = -1.71, SD = 0.04). This suggests that direct calls to purchase reduced the effectiveness of social media messages. The use of information search also reduced the effectiveness of social media messages. The variable representing the use of information search was negative for both likes (β_{Likes} = -1.56; SD = 0.01) and comments ($\beta_{Comments}$ = -2.51; SD = 0.02). Our results indicate that as fanbase size increases, message likes (β_{Likes} = 1.36, SD = 0.01) and comments ($\beta_{Comments}$ = 0.72; SD = 0.01) also increase. The variable representing message time was positive and significant for message likes (β_{Likes} = 0.01, SD = 0.00) and comments ($\beta_{Comments}$ = 0.03, SD = 0.00). This suggests that a longer message time results in more message likes and comments. The variable representing B2B was positive and significant for likes (β_{Likes} = 1.00, SD = 0.01) but was negative and significant for comments ($\beta_{Comments}$ = -1.21, SD = 0.10). This suggests that B2B messages had a higher percentage of message likes than B2C messages whereas B2C messages had a higher percentage of comments than B2B messages.

2.7.2.2.2 Interaction Effects Model

2.7.2.2.2.1 Number of Likes

To test our effectiveness hypotheses, we added the interaction between B2B and message characteristics. We report our results in Table 2.5. We plot the posterior distributions with means and 95% HDIs for interaction terms for likes in Appendix D.

H3 stated that the use of corporate brand names will have a higher percentage of message likes in B2B social media messages than in B2C social media messages. The variable representing the use of corporate brand name was positive and significant for message likes (β_{Likes} = 0.76, SD = 0.04). Thus, H3 was supported as the use of corporate brand name had a higher percentage of message likes in B2B social media messages than in B2C. H4 stated that the use of product brand names will have a higher percentage of message likes in B2C social media messages than in B2B social media messages. The variable representing the use of product brand name was positive but non-significant for message likes (β_{Likes} = 0.01, SD = 0.05). Thus, H4 was not supported.

H7 stated that the use of functional/rational appeals will have a higher percentage of message likes in B2B social media messages than in B2C social media messages. The variable representing the use of functional appeals was positive and significant for message likes (β_{Likes} = 0.22, SD = 0.04). Thus, H7 was supported as the percentage of likes was higher for B2B messages using functional appeals than in B2B messages. H8 stated that the use of emotional appeals will have a higher percentage of message likes in B2C social media messages than in B2B social media messages. The variable representing the use of emotional appeals was positive and significant for message likes

(β_{Likes} = 0.47, SD = 0.03). This is contrary to our hypothesis. H8 was not supported as B2B messages containing emotional appeals had higher percentage of likes.

H10 stated that the use of direct calls to purchase will have a higher percentage of message likes for B2C social media messages than in B2B social media messages. The variable representing the use of direct calls to purchases was negative but non-significant for message likes (β_{Likes} = -0.10, SD = 0.10). This indicates that the hypothesis H10 was not supported.

H12 stated that the use of embedded links and cues for additional information search will have a higher percentage of message likes in B2B social media messages than in B2C social media messages. The variable representing the use of embedded links and cues for additional information was positive and significant for message likes (β_{Likes} = 0.38, SD = 0.05), thus hypothesis H12 was supported.

2.7.2.2.2.2 Number of Comments

Our goal in this research was to explore the encoding process used by B2B buyers/B2C consumers. We measure this process by using Facebook likes and comments. We anticipate observing some differences across liking and commenting of B2B and B2C social media messages for various message strategies. Specifically, we argue that B2B buyers are less likely to comment on messages than B2C consumers. To explore this we tested whether there are differences in the interaction terms for likes and comments. In Appendix D we plot the posterior distributions with means and 95% HDIs. We find differences across message likes and comments for all the interaction terms between B2B and B2C message strategies.

The interaction variables representing the use of corporate brand names ($\beta_{Comments}$ = -2.80, SD = 0.76), product brand names ($\beta_{Comments}$ = -9.98, SD = 5.70), functional appeals ($\beta_{Comments}$ = -1.35, SD = 0.65), emotional appeals ($\beta_{Comments}$ = -0.96, SD = 0.16) and direct calls to purchase ($\beta_{Comments}$ = -8.35, SD = 5.81) were negative and significant. This suggests that B2B buyers are hesitant to comment on social media messages compared with B2C consumers. For the above message strategies, B2B buyers who like the messages are less likely to comment on them. Contrary to our expectation we found that the use of information search was positive and significant ($\beta_{Comments}$ = 1.30, SD = 0.17). B2B buyers have a higher likelihood to comment on messages containing information search cues and links than B2C consumers. This finding suggests that buyers who like the messages containing information search cues and links also make comments. It is possible that the information relayed in the social media messages motivates buyers to post their views or opinions on the information communicated, which further facilitates a dialogue among the buyers, generating more comments.

2.7.3 Discussion

The purpose of study 2 was to test the effectiveness of social media message strategies across B2B buyers and B2C consumers. We tested six hypotheses based on the differences in the encoding process used by B2B buyers and B2C consumers and we found support for three of them. In addition, we explored the effectiveness of social media strategies by measuring the number of message comments.

B2B social media messages containing corporate brand names had a higher percentage of likes than B2C social media messages containing corporate brand names. Indeed, B2B buyers associate themselves with corporate brand names and try to express their identities and attachment with corporate brands by liking messages containing corporate brands. Interestingly, we do not find any difference in the liking of messages containing product brand names across B2B and B2C. This finding suggests that buyers also focus on product brand names. Indeed, the importance of corporate branding has been well established in the B2B purchase decision process (Brown et al. 2011a), however, we find no difference in the effectiveness of product brand strategies in social media strategy across B2B and B2C contexts.

We find that the use of functional appeals in social media messages is more effective among B2B buyers than B2C consumers. This is not surprising as buyers elaborate more on messages containing functional appeals and are more likely to be motivated to like them compared to consumers. However, we find that the use of emotional appeals had higher percentage of likes for B2B messages than B2C messages. This is contrary to the previous belief and research findings which suggest that the use of emotional appeals is more effective in B2C than in B2B (Lothia, Donthu, and Hershberger 2003). Lynch and de Chernatony (2004) state that the use of emotional cues is likely to benefit B2B brands as it might provide a differential advantage and induce customer relationship with existing customers. Indeed, academics have started to emphasize the role and importance of emotional cues in B2B contexts (e.g., Brown et al. 2011b; Rapp et al. 2013).

The use of direct calls to purchase did not prove to be an effective strategy for B2C consumers compared to B2B buyers. This might indicate that both buyers and consumers are less motivated to share content emphasizing commercialism. Social media is an appropriate channel to build relationships where hard sell approaches are least effective. We find that the use of links and cues for information search in B2B social messages was more effective than in B2C social media messages. Buyers rely heavily on information search during their purchasing process and seem to be motivated to share messages containing informational cues that might reduce purchasing risks and help them make sound purchasing decisions.

Furthermore, we find that the liking and commenting behaviors are different across B2B buyers and B2C buyers. B2B messages containing corporate or product brand names, functional or emotional appeals, or direct calls to purchase had a lower percentage of comments than B2C messages containing these strategies. As commenting on messages requires more time and resources, B2B buyers are less motivated to comment on messages compared to B2C messages. Indeed, we find that B2B buyers are less likely to comment on messages but more likely to like messages compared to B2C consumers. It is intriguing to find that B2B messages containing information search cues or links had a higher percentage of comments than B2C messages. Information search is an important part of the buying decision process (Brown et al. 2011a; Gilliland and Johnston 1997) and we suspect that buyers are likely to be more motivated to comment on such messages than B2C consumers. Buyers, being experts in their fields, are likely to express their opinions by commenting on informational messages as well as express their views on the previous comments. As the information conveyed in the messages is very applicable and useful (e.g. white papers, product specs, press releases, and new product launches) in the decision process, commenting on informational messages might be considered as part of the work related activity where buyers feel obligated to share their views and opinions (Bruhn, Schnebelen, and Schafer 2013).

2.8 General Discussion

B2B marketers have started to use social media in their marketing efforts to interact with their buyers. This is not surprising as B2B marketers believe that communicating with buyers on social media can help build brand awareness and loyalty, customer relationships, enhance reputation, and even generate potential leads (Michaelidou, Siamagka, and Christodoulides 2011; Bruhn, Schnebelen, and Schafer 2013). Besides, B2B buyers have started to use social media in their decision process and expect interactions on social media sites from businesses (Rapp et al. 2013). However, B2B marketers are struggling with the successful implementation of social media in their marketing activities and are likely to adopt strategies used in traditional outlets or follow the lead of their B2C counterparts (Michaelidou, Siamagka, and Christodoulides 2011; Rapp. et al. 2013). In this research we attempt to provide some guidance to marketing managers who are responsible for social media communications. Specifically, we investigate the usage (study 1) and effectiveness (study 2) of communication strategies that B2B marketers should implement that will help their brands.

This research contributes to the existing literature by better understanding the communication flow of social media and highlighting the key communication strategies that are likely to motivate B2B buyers/B2C consumers to share brand content. We draw from multiple theoretical perspectives. We adapt the Shannon and Weaver (1949) communication model to the social media context to frame the communication flows (Yadav and Pavlou 2014). Then, we rely on the WOM (psychological motivations), organizational buying and B2B advertising theories to highlight key differences across B2B and B2C contexts and identify effective communication strategies for B2B marketers. We argue that B2B marketers use different branding, message appeals, selling and informational strategies in their communications. We find that B2B communications have a higher likelihood to contain corporate brand names and informational search cues and links than B2C messages. In addition, we find that B2C messages have a higher likelihood to contain product brand names, emotional appeals, and convey more direct calls to purchases than B2B messages. Furthermore, we find that the use of corporate brand names is more frequent than the use of product brand names in B2B messages. Indeed, the importance of corporate branding is gaining importance in B2B buying process as corporate brands can help reduce performance and economic risks thus facilitating ease in the decision process (Brown et al. 2011a; 2011b). We find that there were no differences in the use of functional and emotional appeals in B2B messages. Indeed, using emotional appeals can help brands create a differential advantage and facilitate relationship building in social media (Rapp et al. 2013; Lynch and de Chernatony 2003).

Importantly, we test the effectiveness of these message strategy practices in B2B and B2C contexts by measuring the number of message likes and comments. Our rationale is to evaluate the decision process that occurs after customers are motivated to share the content – whether to like and/or comment on the messages? To our best knowledge, this is the first study to incorporate and differentiate two measures of effectiveness for B2B and B2C social media messages. We argue that liking a message is a different behavior than commenting on a message. We further argue that B2B buyers are less likely to comment on messages than B2C consumers. As commenting requires more time and resource allocation, buyers, compared to consumers, are hesitant to comment on messages given their highly involved, cognitive nature of the buying process. Our results indicate that buyers like messages more frequently than consumers whereas consumers comment on messages more frequently than buyers. Furthermore, we do find differences across liking and commenting between buyers and consumers for various message strategies. This furthers our understanding of B2B social media phenomena by finding differences across liking and commenting for buyers and consumers.

B2B buyers like messages containing corporate brand names, functional appeals, emotional appeals, and informational cues and links more frequently than B2C consumers. It is interesting to note that emotional appeals had higher percentage of likes for B2B messages than B2C messages. Buyers are motivated to share emotional content by liking them. Buyers do rely on emotional cues in their buying decision process (Lynch and de Chernatony 2004; Brown et al. 2011b) and companies use such emotional cues to build relationships with existing customers and try to create a differential advantage among competitors. Thus, in new mediums such as social media, emotional appeals seem to be more prevalent and effective in the B2B context. We did not find any difference in the percentage of likes for messages using direct calls to purchase and product brand names for B2B and B2C social media messages. For these message strategies, the motivational level to share messages is likely to be similar across buyers and consumers.

Buyers are less likely to comment on social media messages than consumers. For all message strategies under examination but one, informational cues and links, we find that B2B messages had fewer percentage of comments than B2C. Buyers like to share their opinions on the information related in the messages by commenting on them. We believe that buyers might fulfill their functional needs such as the need for information, ideas and problem solving through commenting on informational messages (Bruhn, Schnebelen, and Schafer 2013). Besides, buyers might feel morally obligated to each other and in the process comment on informational messages.

2.8.1 Managerial Implications for B2B

In Table 2.6 we highlight our key findings and provide managerial implications for B2B managers. We focus on providing guidance to B2B marketers on the social media communication strategies to implement when communicating with their buyers and prospects. The success of any social media site is realized when users read the brand messages and is enhanced when they share it with their networks of friends (Berger and Milkman 2012). Indeed, it becomes critical for B2B marketers to craft communication strategies that are likely to motivate their customers engage with their messages and spread them throughout their networks.

We find that B2B buyers like messages more frequently than B2C consumers whereas B2C consumers comment on messages more frequently than B2B buyers. Commenting on messages requires more time and effort and it might even deplete cognitive resources. Given that the B2B buying process is highly involved, requires substantial cognitive resources and has higher perceived risks compared to the B2C buying process, buyers are less likely to comment on messages compared to consumers. Thus, B2B communication effectiveness recommendations are primarily driven through the liking of messages.

2.8.1.1 Branding Strategy

Our results indicate that the use and effectiveness (likes) of corporate brands was more frequent in B2B social media messages than in B2C. Likewise, the use of product brand names was less frequent in B2B social media messages than in B2C social media messages. We recommend that B2B marketers highlight their corporate brand names in their social media messages. Buyers are more likely to be motivated to share content containing corporate brands. As marketers use social media to increase their brand measures through loyalty, awareness, credibility and relationships, the use of corporate brand name is recommended. The use of product names is less likely to be effective for B2B messages. Corporate brands reduce the perceived risks in the decision process as they communicate both tangible and intangible attributes of the offering (Brown et al. 2011b). This advantage is least likely to occur with just the use of product band names. It is important to note that the use of corporate brands and product brands had a lower percentage of comments. Using brand names might reduce the number of comments.

2.8.1.2 Message Appeals

We find that the use of functional and emotional appeals had a higher percentage of likes in B2B messages than in B2C messages. Furthermore, B2B marketers use a lower percentage of emotional appeals in their communications than B2C marketers, and we found no differences in the use of functional appeals. It is noteworthy to find that the percentage use of functional appeals and emotional appeals were similar within B2B practices. Based on these findings we recommend that B2B marketers use both functional and emotional appeals. It is likely that functional appeals are more appropriate for prospects who are looking for information on new products/services, whereas emotional appeals are more appropriate for existing customers as they might help build relationships (Rapp et al. 2013). Indeed, B2B scholars have started to explore the importance of using emotional cues to influence B2B buyers as they might help companies gain a differential advantage (Lynch and de Chernatony 2004). Our results indicate that the use of messages appeals had a lower percentage of comments. Using functional and emotional appeals might reduce the number of comments.

2.8.1.3 Selling Strategy – Direct Calls to Purchase

We recommend that B2B marketers refrain from the use of direct calls to purchase or hard sell approaches in their social media communications. Our results suggest that B2B marketers are less likely to use such approaches in their communications than B2C marketers and that using them reduces the percentage of likes and comments. Buyers are less prone to impulsive buying behavior due to a highly involved and cognitive buying decision process. Moreover, buyers might even avoid company websites that use hard sell commercialism to a point that they may never return to them (Spekman and Dotson 2009). Indeed, buyers are hesitant to respond positively to social media communications that use such approaches. It is noteworthy to see such a low usage of hard sell approaches in B2B messages. This suggests that B2B marketers do not use social media as a selling tool.

2.8.1.4 Information Search

Our results indicate that there is more use and greater effectiveness (for both likes and comments) of cues and links for information in B2B social media messages compared with B2C messages. Buyers rely on information search to make a rational purchase and reduce decision risks (Brown et al. 2011b). Indeed, it is not surprising to note this behavior in buyers given their expertise in their fields (Gilliland and Johnston 1997). Information search is an important part of the buying process and B2B buyers have started to use social media, primarily to search for current information on brands and products/services (Rapp et al. 2013; Mudambi, Doyle, and Wong 1997). We recommend that B2B marketers share information such as technical cut sheets, white papers, news articles, information on new products/services through links and cues on social media sites. It is noteworthy to find that a higher percentage of comments were observed for B2B messages using cues and links for information search. We recommend that marketers interested in gaining customer insights through comments use links and cues for information search in their social media communications.

2.8.2 Limitations and Future Research

In evaluating this research, there are limitations that need to be considered as well as potential directions for the future research. First, our sample size is comprised of Fortune-500 Facebook company wall posts which do not necessarily generalize to other social media sites as well as to specific industries or small businesses. As each social media site follows different architecture, purpose and customer value, it would be interesting to test the B2B and B2C message strategies on other sites such as Twitter, Google+, and LinkedIn. Additionally, investigating the practices and the effectiveness of social media communications for small businesses and specific industries will better our understanding of B2B social media phenomena.

Second, our data consisted of one week of Facebook posts, which is less likely to capture the changes in the behaviors of buyers and consumers as well as the practices across B2B and B2C marketers. In our analysis we do not capture this effect. Our goal in this research was to provide guidance to B2B marketers on the execution of social media communications. The amount of data collected was sufficient for empirical investigation. Indeed, one important avenue for research would be to track the changes in B2B social media practices over time.

Third, in our analysis we captured the number of comments and did not categorize the valence of comments. Although our goal was to capture the popularity of brands posts, we view the exclusion of valence of comments as a potential limitation.

Fourth, we did not control for individual characteristics of fans and their networks of friends who liked and commented on messages. Identifying and controlling for these effects is both methodologically and statistically challenging. Although our goal was to test the differences between B2B buyers and B2C consumers, in general, we consider this omission as a potential limitation. Future research could conduct experiments based on our findings by controlling for individual characteristics in order to validate our results.

Fifth, we explored two modes of communication that users use ubiquitously to measure message effectiveness – likes and comments. It would be interesting to test our hypotheses for other measures such as Google+1, likes versus dislikes, and retweets. Furthermore, we found differences in the use of likes versus comments for B2B marketers. It would be worthwhile to further explore the comments on messages sent by the companies. Marketers could use this information to improve customer insights regarding what customers have to say about their brands, products and services and in the process it could provide vital information on competition.

Sixth, we investigated communication strategies related to branding, message appeals, selling and information search. It would be interesting to investigate additional strategies such as the use of images and videos, categories of emotional and functional appeals as well as the linguistic styles used that might help managers improve their brand engagement on social media. Specifically, we encourage academics to identify important strategies that B2B marketers could implement to increase the number of comments. What message strategies should B2B marketers promote to initiate customers-to-customer interactions that will help their brand? We believe that this will be an important topic to explore.

Seventh, it would be interesting to explore other effective B2B social media strategies beyond likes. Specifically, how does liking messages/content help in improving marketing outcomes (e.g. brand loyalty, awareness, and equity) and financial outcomes (sales, stock price and generation of leads) in the B2B context? Our findings regarding effective communication strategies might help academics to explore this question.

In conclusion, our objective in this research was to improve our understanding of B2B social media phenomena. In the process we identified and found some differences in the use and effectiveness of message strategies across B2B and B2C contexts. This research responds to the call for research into B2B social media. Given the dearth of research on this topic, we hope that our findings enrich future research that explores the B2B social media phenomena.

Table 2.1
Research Overview

Study	Social Media Message Strategies	Business Type (B2B versus B2C)
Study 1 Social Media Message - Practices	Branding	
	Company Brand Name	H1
	Product Brand Name	H2
	Message Appeals	
	Functional Appeal	H5
	Emotional Appeal	H6
	Selling Strategy	H9
	Information Search	H11
Study 2 Social Media Message - Effectiveness	Branding	
	Company Brand Name	H3
	Product Brand Name	H4
	Message Appeals	
	Functional Appeal	H7
	Emotional Appeal	H8
	Selling Strategy	H10
	Information Search	H12

Table 2.2
Social Media Message Strategy Executions for B2B and B2C

	Number of Messages		Percentage of Total Messages	
Message Strategy	**B2B**	**B2C**	**B2B**	**B2C**
Corporate Brand Name	135	309	41.4%	27.1%
Product Brand Name	64	298	19.6%	26.1%
Functional Appeals	75	178	23.0%	15.6%
Emotional Appeals	87	697	26.7%	61.1%
Direct Calls to Purchase	12	186	3.7%	16.3%
Information Search	289	894	88.7%	78.4%
Total Messages	326	1,141	100%	100%

Table 2.3
Study 1 – Logistic Regression Results

Dependent Variable: B2B Communications

Message Strategy	**Estimate**[a]	**SD**	**Hypotheses**
Intercept	**-1.22**	0.19	
Corporate Brand Name (1=yes)	**0.67**	0.15	H1 – Supported
Product Brand Name (1=yes)	**-0.41**	0.18	H2 – Supported
Functional Appeals (1=yes)	0.33	0.18	H5 – Not Supported
Emotional Appeals (1=yes)	**-1.27**	0.15	H6 – Supported
Direct Calls to Purchase (1=yes)	**-1.30**	0.32	H9- Supported
Information Search (1=yes)	**0.51**	0.20	H11 – Supported

[a]Bold estimate indicate that 95% HDI did not contain zero value.

Table 2.4
Descriptive for Message and Facebook Account Variables

Message and Account Variables	**B2B**	**B2C**
Mean Message Likes	19 (65)	621 (5,515)
Mean Message Comments	2 (8)	78 (341)
Mean Message Time (minutes)	466 (313)	484 (360)
Mean Fanbase	80,874 (497,956)	1,700,903 (3,793,071)

Note – Values rounded to nearest 1. Standard deviations reported in parenthesis.

Table 2.5
Study 2 – Bivariate Poisson Results

	Main Effects Model				**Interaction Effects Model**				
	Likes		**Comments**		**Likes**		**Comments**		**Hypotheses**
Message Strategy	**Estimate[a]**	**SD**	**Estimate[a]**	**SD**	**Estimate[a]**	**SD**	**Estimate[a]**	**SD**	**Likes**
Intercept	**-13.23**	0.04	**-6.67**	0.06	**-13.28**	0.04	**-6.72**	0.06	
Corporate Brand Name (1=yes)	**-0.27**	0.01	**-0.25**	0.01	**-0.28**	0.01	**-0.25**	0.01	
Product Brand Name (1=yes)	**-0.25**	0.01	**0.20**	0.01	**-0.25**	0.01	**0.20**	0.01	
Functional Appeals (1=yes)	**0.01**	0.00	**-0.47**	0.02	0.00	0.01	**-0.47**	0.02	
Emotional Appeals (1=yes)	**0.59**	0.01	**1.51**	0.02	**0.58**	0.01	**1.53**	0.02	
Direct Calls to Purchase (1=yes)	**-0.59**	0.01	**-1.71**	0.04	**-0.59**	0.01	**-1.73**	0.04	
Information Search (1=yes)	**-1.56**	0.01	**-2.51**	0.02	**-1.56**	0.01	**-2.50**	0.02	
Fanbase	**1.36**	0.00	**0.72**	0.00	**1.36**	0.01	**0.72**	0.01	
Message Time	**0.01**	0.00	**0.03**	0.00	**0.01**	0.01	**0.03**	0.01	
B2B (1= B2B, 0 = B2C)	**1.00**	**0.01**	**-1.02**	**0.10**	**0.26**	0.06	**-0.32**	0.17	
B2B × Corporate Brand Name					**0.76**	0.04	**-2.80**	0.76	H3 –Supported
B2B × Product Brand Name					0.01	0.05	**-9.98**	5.70	H4 – Not Supported
B2B × Functional Appeals					**0.22**	0.04	**-1.35**	0.65	H7 –Supported
B2B × Emotional Appeals					**0.47**	0.03	**-0.96**	0.16	H8 – Not Supported
B2B × Direct Calls to Purchase					-0.10	0.10	**-8.35**	5.81	H10 – Not Supported
B2B × Information Search					**0.38**	0.05	**1.30**	0.17	H12 – Supported

[a]Bold estimate indicate that 95% HDI did not contain zero value.

Table 2.6
Summary of Findings and Managerial Implications for B2B

Message Strategy	Dominant Communication			Managerial Implications for B2B
	Usage	Effectiveness		
		Likes	Comments	
Branding				
Corporate Brand Name	B2B	B2B	B2C	Highlight corporate brand names to generate more likes.
Product Brand Name	B2C	No Difference	B2C	Refrain from using only product brand names.
Message Appeals				
Functional Appeals	No Difference	B2B	B2C	Highlight functional appeals to generate more likes.
Emotional Appeals	B2C	B2B	B2C	Highlight emotional appeals to generate more likes.
Selling Strategy (Hard sell)	B2C	No Difference	B2C	Refrain from using hard selling approaches.
Information Search	B2B	B2B	B2B	Highlight informational cues and links to generate more likes and comments.

Figure 2.1
Social Media Communication Model

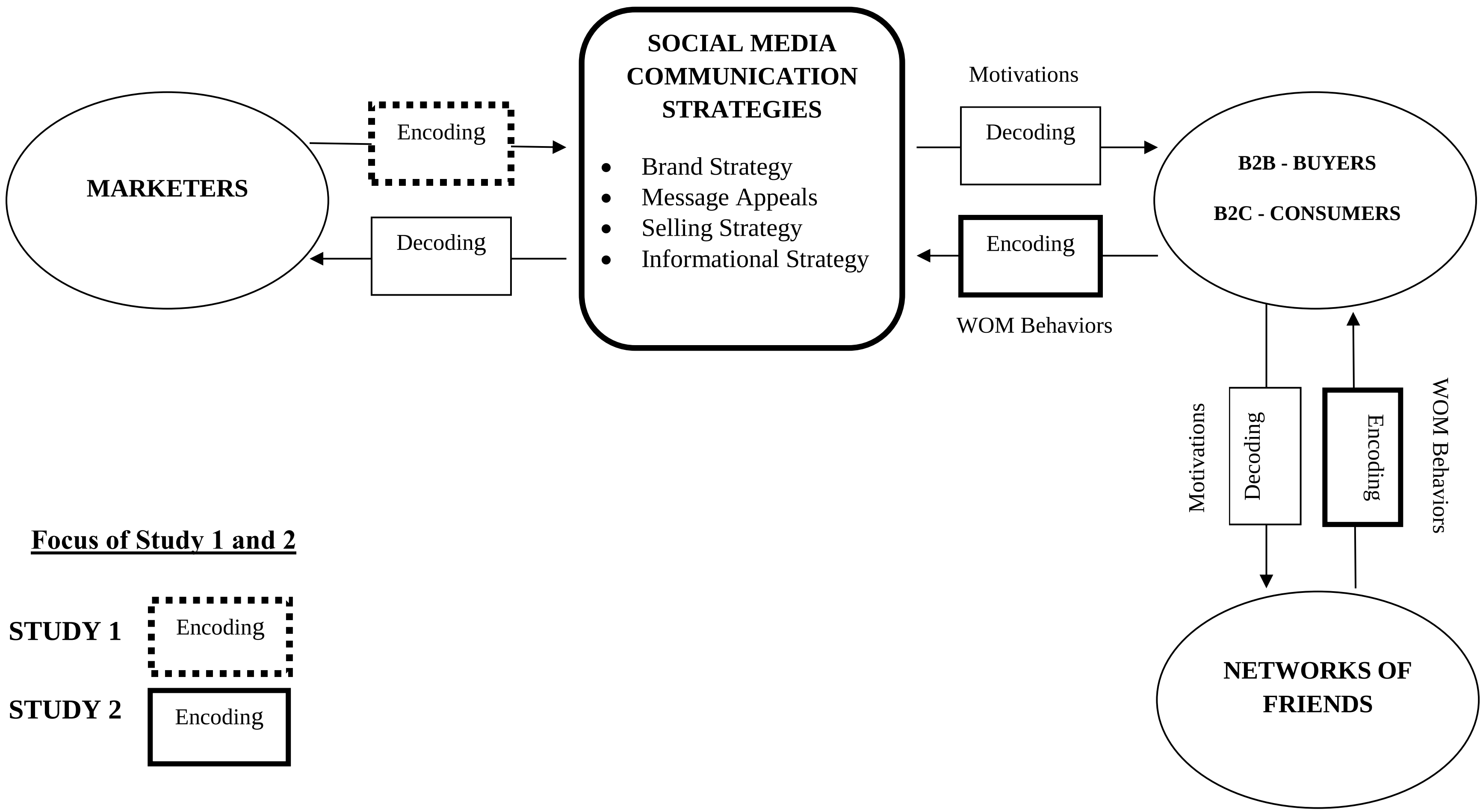
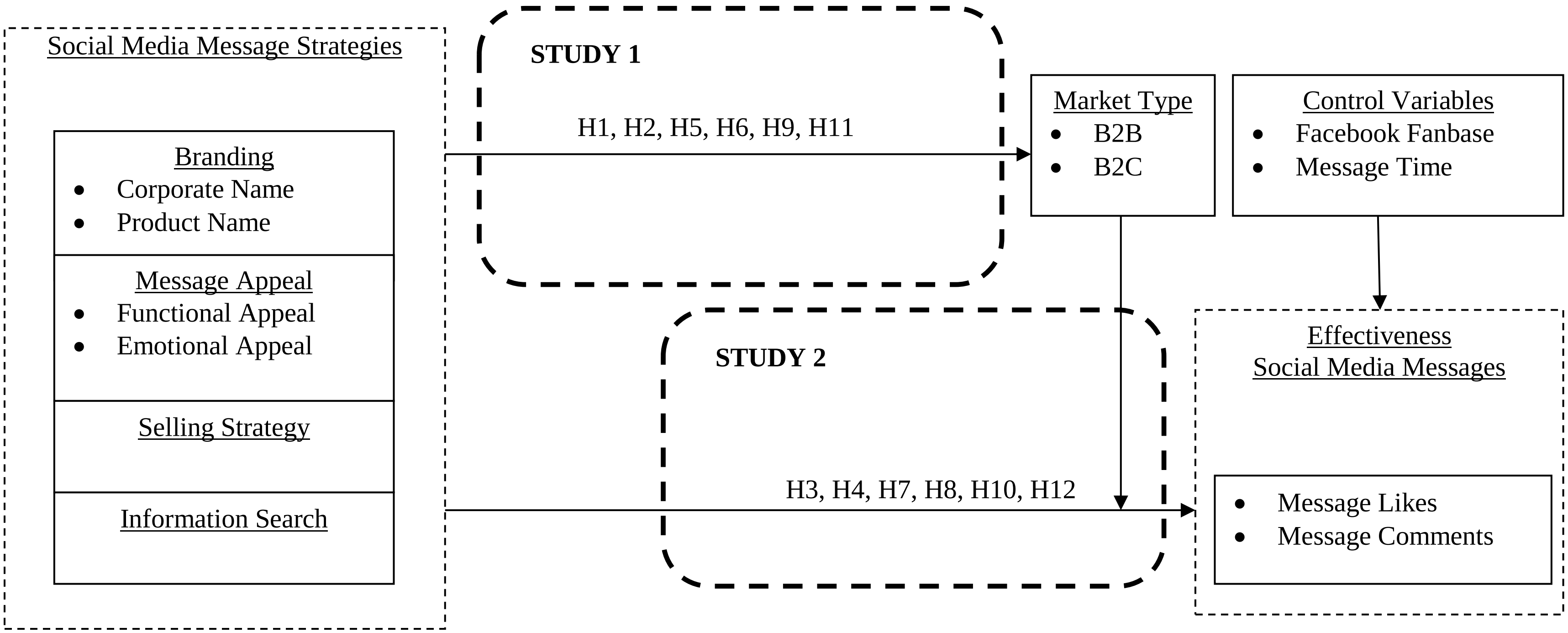


Figure 2.2
Overall Empirical Model



CHAPTER 3

ASSESSING THE LEVELS OF SOCIAL MEDIA MESSAGE EFFECTIVENESS FOR SERVICES AND PRODUCTS

3.1 Introduction

There can be challenges associated with advertising services due to their unique nature of intangibility, difficulty in evaluations before purchases, heterogeneity, perishability, often inseparability, and higher risk than is associated with goods (Zhu and Zhang 2010; Zeithaml, Berry and Parasuraman 1985; Sweeney, Soutar, and Mazzarol 2012). Based on these unique characteristics, prior research has argued that services, when compared to products (goods), are likely to use different brand strategies, message appeals and tangibilizing strategies (Aaker 2004; Mortimer 2008; Stafford 2005).

Indeed, marketing services is more challenging than products. Given its complex nature, services have increasingly relied on word-of-mouth (WOM), which is likely to help in reducing associated risks and shaping the expectation of services when making purchasing decisions (Sweeney, Soutar, and Mazzarol 2012; Bansal and Voyer 2000). Further, consumers have started to rely more on informal and/or personal communication sources (social networks) than on traditional advertising outlets in making their purchase decisions (Bansal and Voyer 2000; Trusov, Buclin and Pauwels 2009; Kumar and Mirchandani 2012), which, in turn, makes marketing more challenging. It is estimated that twenty to fifty percent of purchasing decisions are influenced by WOM (Berger 2013). With the rise and usage of social media, these interpersonal communications

(WOM) have greater impact on consumer decision making. Indeed, marketing services on social media sites is critical.

In this changing environment, marketers have started to utilize social networks to spread their brand messages through interpersonal communications (Berger 2013). To induce brand communications and content sharing, marketers create brand communities on social media sites where consumers can interact with company brand communications by liking, commenting, tweeting, and/or sharing content (de Vries, Gensler, and Leeflang 2012). The utility of any social media site is derived when its users transmit brand related content by spreading WOM (Berger and Milkman 2012). Furthermore, the transmission of WOM among consumer networks is critically important as research suggests causal impact of WOM on sales, purchase intentions and product adoption (Zhu and Zhang 2010; Chevalier and Mayzlin 2006; Godes and Mayzlin 2009; Liu 2006; Trusov, Buclin, and Pauwels 2009; Stephen and Galak 2012; Naylor, Lamberton and West 2012). For marketers, understanding under what conditions users transmit content and using which forms of new communication is essential. Given the significance of WOM in advertising services, it is important to identify effective communication strategies that marketers should adopt to make the highest impact.

What social media strategies should marketers implement when offering services versus products? We address this question in this essay. In particular, we investigate the effectiveness of traditional advertising strategies in terms of brand strategies, message appeals, and the use of vividness to tangibilize offerings in a social media environment. Our focus is to examine *how* and *when* the social media communications get transmitted. In particular, to answer "how," we focus on the two modes of transmissions, message likes and comments. To answer “when,” we examine how offering characteristics, products versus services are likely to affect the social transmission of content. We argue that the transmission of social media communications is likely to be affected by offering characteristics. We contend that the effectiveness of social media communications across products and services depends upon the use of branding strategy, use of message appeals and use of vividness. Our empirical investigation analyzes 1,467 Facebook message posts of Fortune-500 companies and tests their effectiveness by measuring the number of message likes and comments. Based on this analysis, we classify each Facebook company account (brand community) (Zaglia 2013) as offering either services or products and test the moderating effects of offering type on effectiveness of various message strategies based on branding, message appeals, and the use of vividness.

This essay is organized as follows: (1) we summarize previous research to help us put our contributions in perspective, (2) we provide our theoretical framework using communication theory to help understand the flow of communication in a social media context, (3) we highlight the differences between services and products offering and state our hypotheses using service advertising and WOM literatures, (4) we test our hypotheses by estimating Multivariate Multilevel Poisson Model and report our results followed by discussion, and (5) we provide managerial implications along with limitations and directions for future research.

3.2 Research Background

WOM communication has been studied empirically through various research perspectives (Brown, Barry, Dacin, and Gunst 2000; Lindgreen, Dobele, and Vanhamme 2013; Lovett, Peres, and Schachar 2013). Social networks theory has been used widely to study role of the sender and the end user (receiver) in WOM networks (Brown and Reingen 1987; Brown, Broderick, and Lee 2007; Duhan, Johnson, Wilcox, and Harrell 1997; Abrantes, Seabra, Lages, and Jayawardhena 2013). In particular, several researchers have studied the influencing interpersonal and/or non-interpersonal factors related to source/receiver characteristics (Brown, Barry, Dacin, and Gunst 2000; Zhu and Zhang 2010; Zhang, Craciun, and Shin 2010; Chakravarty, Liu and Mazumdar 2010; Bansal and Voyer 2000; Wangenheim and Bayon 2007). Likewise, research has also been able to identify some of the antecedents to the WOM communications such as satisfaction, loyalty, quality and commitment (de Matos and Rossi 2008). Diffusion researchers identify WOM to be the primary driver of new innovations (Brown, Barry, Dacin, and Gunst 2000; Lopez and Sicilia 2013). The diffusion research stream has focused on the role and influence of opinion leaders and hubs in the new product adoption and innovation process as well as the importance of WOM communications in new product adoptions (Martin and Lueg 2011; Goldernberg, Han, Lehmann and Hong 2009; Lopez and Sicilia 2013).

Researchers have also examined consumer motivations behind WOM behaviors. Several researchers have identified the intrinsic and extrinsic motivations (Hennig-Thurau, Gwinner, Walsh, and Gremler 2004; de Angelis, Bonezzi, Peluso, Rucker, and Costabile 2012; Phelps, Lewis, Mobilio, Peery, and Raman 2004; Ho and Dempsey 2010; Alexandrov, Lilly, and Babakus 2013; Lovett, Peres, and Schachar 2013) that inspire consumers towards WOM behaviors. Hennig-Thurau et al. (2004) found social interactions, desire for economic incentives, concern for other consumers, and the potential to enhance the self-worth as primary factors leading to WOM behaviors among consumers.

Researchers have also highlighted the outcomes of WOM (Luo 2007; Villanueva, Yoo, and Hanssens 2008; Chevalier and Mayzlin 2006; Kumar and Mirchandani 2012; Liu 2006; Stephen and Galak 2010). Primarily, this research stream has investigated the financial and marketing outcomes of WOM communications in terms of sales, stock price, customer life time value, brand awareness, and ROI, and has also compared the WOM influence with traditional marketing (Feng and Papatla 2011; Stephen and Galak 2010; Trusov, Buclin, and Pauwels 2009). Indeed, WOM has positive influence on financial and marketing outcomes.

Another perspective on WOM and the most relevant to our study is the research stream that has focused on content that is most likely to be transmitted (viral) or that initiates WOM (Berger and Milkman 2012; Berger 2011; Phelps, Lewis, Mobilio, Peery, and Raman 2004). This research stream has investigated the content of the stimuli and its propensity to get transmitted within a social network (de Vries, Gensler, and Leeflang 2012). Primarily, researchers have investigated the content of emails (Phelps et al. 2004; Chiu, Hseih, Kao, and Lee 2007), news articles (Berger and Milkman 2012; Chen and Berger 2013; Berger 2011), TV ads (Porter and Golan 2006), viral campaigns (Dobele, Lindgreen, Beverland, Vanhamme, and Wijk 2007), and, recently, social media brand posts (de Vries, Gensler, and Leeflang 2012; Smith, Fischer and Yongjian 2012) to study effective WOM communications. We review the key selected research articles in Table 3.1. This table reports the variety of ways researchers have measured, inferred or captured WOM interactions. The table also reports the WOM context, incorporation of moderators, modes of transmission of WOM, statistical methods implemented and the key relevant findings.

The most prevalent finding suggests that provocative emotional content is more likely to be transmitted by individuals (Berger and Milkman 2012; de Vries, Gensler, and Leeflang 2012; Phelps et al. 2004; Chiu, Hseih, Kao, and Lee 2007; Porter and Golan 2006). Content that arouses emotions such as awe, anger, or anxiety, and are seen as entertaining and funny seem to be transmitted more by consumers (Berger and Milkman 2012; Phelps et al. 2004). Dobele et al. (2007) assert that surprise and emotions both trigger transmission of content thus making it viral. They find that disgust and fear messages are transmitted more by men than by women. Berger and colleagues, taking a more psychological approach, find that interesting products get more immediate WOM, however they do not receive more ongoing WOM as time elapses. They find that products which are made aware by the environmental cues, or are made publicly visible, receive more WOM that is immediate and enduring (Berger and Schwartz 2011). Chen and Berger (2013) find that moderate controversy is likely to create more conversations, suggesting that the effect is enhanced when an individual's identity is not disclosed and also when the conversation takes place with a friend. De Vries, Gensler, and Leeflang (2012) analyzed the content of 11 brand posts on Facebook and found that vivid and interactive brand posts can increase Facebook likes, whereas interactive posts (e.g., questions) can boost comments. In sum, this research stream has contributed by identifying the features/content of the messages as well as the characteristics of the settings and context that is likely to make the content go viral.

Despite the extensive research on WOM, research on content that stimulates WOM behaviors has primarily focused on main effects in the absence of key moderators (Libai, Bolton, Bügel, Ruyter, Götz, Risselada, and Stephen 2010; Berger and Schwartz 2011; Dobele et al. 2007; Chen and Berger 2013). There is a dearth of research on content and WOM using moderators; and that which has been done is mostly situational and in experimental settings (Chen and Berger 2013). Indeed, there are calls to study moderating effects on WOM communications (MSI 2012; Lindgreen, Dobele, Vanhamme 2013). For example, MSI (2012) invited, "Research [that] is needed to understand how different consumer groups respond to different communications activities [WOM marketing] for different categories and markets." In addition, despite various calls to study social media in depth (Libai et al. 2010; Lindgreen, Dobele, Vanhamme 2013), research on WOM communications in social media and services is very limited given the importance of WOM in services (Refer to Table 3.1).

This study explores new ground in both research objectives and applications. First, communication theory is tested in an interactive environment such as social media (Yadav and Pavlou 2014). Second, communication and WOM theories are applied to deepen our understanding of various message strategies that are likely to influence modes of social transmission, and the subsequent spreading of WOM among consumer networks. Third, the effects of a key moderator, products and services on various message strategies are assessed, thus contributing to the WOM and service advertising literatures. Fourth, simultaneously two modes of transmission, message likes and comments are modeled by introducing and estimating a Multivariate Multilevel Poisson Regression Model which allows one to model multiple outcomes variables in a nested data structure. This extends prior research which has measured or analyzed only *one* mode of transmission of WOM, including studies related to social media where multiple modes of transmission are prevalent (de Vries, Gensler, and Leeflang 2012). Fifth, given the active presence of Fortune-500 on social media sites (Barnes and Lescault 2012; Barnes, Lescault, and Wright 2013), our sample data frame provide better insights and generalizability of effective WOM marketing communications for large businesses and top global brands. This research provides significant and directly applicable implications for managers to improve their social media communication effectiveness, especially in a services context.

3.3 Social Media Communications

To understand effective WOM communications, it is essential to understand the flow of communication that occurs in social media sites. We use communication theory to explain the transmission of content that occurs in social media (Yadav and Pavlou 2014). Communication theory states that a *source* encodes (creation) a message and then transmits through a *medium* (Shannon and Weaver 1949; Ducan and Moriarty 1998; Hoffman and Novak 1996; Lasswell 1948; Stern 1994). The transmitted message is received by the receiver who decodes (processes) the message. Furthermore, in an interactive medium the receiver, after decoding encodes the message and sends/directs it back to the sender, and, in the case of social media, perhaps to others. This is a feedback loop that occurs between the receiver and the sender (Mueller, Garg, Nam, Berg, and McDonnell 2011).

In an interactive medium such as social media, a source of a message is the marketer who creates/constructs (encodes) a message and sends it to their intended audiences. Consumers read and process the message/information (decode) and are likely to take appropriate action such as transmitting/sharing/spreading (encode) the message to their networks of friends, or even back to the source by (in social media vernacular) liking, commenting, tweeting and more. The encoding process adopted by marketers is critical as it is likely to affect the decoding process and, subsequently, the encoding process of consumers. Thus, marketers have to use appropriate message strategies so that their intended audience can make sense of the messages that come through it (Dennis, Fuller, and Valacich 2008) and subsequently be motivated to share the message positively with their networks of friends – spread the word of mouth.

In Figure 3.1 we present the flow of communication that occurs between marketers and their consumers on social media sites. Unlike traditional communication models, the social media communication model incorporates the role of networks of friends. The marketers encode the message based on the offering type (services versus products) and send appropriate messages incorporating brand strategy, message appeals, and vividness to its target audience through social media. They promote brand names in their communications to increase brand awareness and loyalty, and use various message appeals and/or vividness in their communications to entice audiences to interact with the messages to increase engagement (de Vries, Gensler, and Leeflang 2012).

Consumers desire to engage in WOM communications is driven by several motivations, such as supply of information, the need to express uniqueness, self-enhancement, communicate identity, desire to converse, express uniqueness and satisfaction and the concern for other consumers (Berger and Milkman 2012; Hennig-Thurau et al. 2004; Lovett, Peres, and Shachar, 2013). When the target consumer receives brand messages they decode them (message processing). During the decoding process, underlying psychological motivations help consumers to decide whether to share the brand messages. These psychological motivations may be more salient in some situations than others.

We argue that these motivations are likely to be activated by appropriate message strategies used by marketers when offering services versus products. Thus marketers are best served by matching the message strategies with the underlying psychological motivations to spread the WOM. Once the consumer is motivated to spread the WOM for brand, s/he needs to determine how to engage with the brand message and eventually share it with a network of friends. We argue that the decision of how to engage with the brand message will either follow a system 1 or system 2 process (Evans 2008; 2011; Kahneman 2011). The system 1 process is fast, unconscious, intuitive, impulsive, and reflexive, whereas the system 2 process is slow, conscious, analytic, and reflective (Evans 2008). Depending upon the process, system 1 or system 2, the consumer can create a response, like, share, or even comment on the brand message. These consumer actions are the encoding process in our model. This consumer message, which is a response to the marketer message, is then transmitted to, and received by, the consumer's network of friends as well as the primary source of the message, the marketer. This is the feedback loop that occurs between consumers and their networks of friends and the marketers. In this research we focus on the feedback loop that occurs primarily between consumers and their networks of friends. The networks of friends also follow the similar process of decoding and encoding explained earlier.

Value for the marketer is derived when social media users transmit content that helps the brand (Berger and Milkman 2012). Marketers can realize this value by creating appropriate message tactics based on brand strategies, message appeals, and the use of vividness to persuade and motivate their audience to positively transmit the messages among their networks through various modes. The selection of appropriate message tactics thus depends upon on how consumers are likely to decode (e.g., a function of saliency of psychological motivations) and then encode the messages to transmit WOM. We suggest that consumers will use different decoding and encoding processes when considering either services or products.

Scholars have documented the key differentiating factors between products and services (Zeithaml, Parasuraman, and Berry 1985; Berry 1980; Lovelock 1981). This has led several research streams to recommend treating differently advertising executions for services and products (e.g. Stafford 1996; Stafford 2005; Turley and Kelly 1997; Mortimer 2008; Tripp 1997). Services differ from products as they are more heterogeneous, intangible, often inspirable (Keh and Pang 2010), perishable (Zeithaml, Parasuraman, and Berry 1985), and they have higher associated risks (Bansal and Voyer 2000). These differences affect the execution of services communications that result in the use of different branding strategy, message appeals, and the use of vividness in their advertising executions. Scholars have documented that the use of company brand name is more effective for companies delivering services (Aaker 2004). Further, emotional appeals are more likely to be effective in services advertising (Mortimer 2008); whereas the use of vividness (images and videos) for visually tangibilizing the services rendered seems to be less effective in services advertising (Stafford 1996).

Marketers use various communication strategies on social media sites to motivate consumers to spread brand messages. Marketers have the option to choose strategies based on branding, message appeals, and the use of vividness in their communications. Based on the above discussion, we outline various message strategies that are likely to motivate consumers to spread WOM when offerings vary from services to products in a social media environment. For example, motivation to express the need for uniqueness, social identity and/or self-enhancement is likely to be more salient for service messages with corporate brand names. In addition, motivation to express emotional needs, such as excitement, satisfaction, and a feel good factor, are likely to be more salient for services messages with emotional content (Lovett, Peres, and Shachar 2013). These motivations stimulate WOM behaviors. Thus, we expect consumers and their networks of friends to transmit messages using corporate brand names and emotional appeals when considering services. We test this encoding process of consumers and their networks of friends (Refer to Figure 3.1).

In Figure 3.2 we present our empirical model. Our model is closely related to the psychological choice model (Hansen 1976) in which the effectiveness of an influencer (message strategies) is moderated by the contextual effects (offering characteristics), and in which this interaction among the variables determines the response (encoding of message) (Zhu and Zhang 2010). Marketers use various branding, message appeals, and tangebilizing strategies (use of vividness) in their social media executions. We expect these strategies to motivate consumers to transmit the content to their networks of friends via liking and/or commenting of the messages. In addition, we expect that offering type, characterized as either services or products, is likely to moderate the encoding process of the consumers and their networks of friends. Social media messages are nested within a company's social media accounts. Thus, the model has a two level hierarchical structure.

3.4 Modes of Encoding

Social media sites offer their users various modes for transmitting the content to their networks of friends. These modes of transmission~~s~~ are referred to as social plugins, with which users can share their opinions with their friends. Social plugins can be broadly differentiated into two categories, (1) one-click social plugins which allow relatively frictionless transmission of content, and (2) composition-based social plugins which allow a deeper mode of engagement. One-click social plugins are buttons placed on social media or other sites through which users can share their interest or convey their attitude about various content through just one click (e.g. Like, Google+1, Retweet, and Share). On the other hand, composition-based social plugins, such as comments on social media sites, involve deeper engagement as users express opinions with more dimensions by having their say. Further, one-click social plugins (e.g, like) will tend to require less cognition than do composition-based social plugins (e.g., comments), where users need to cognitively process information in order to express their opinions.

Consumers motivated to spread WOM on brands need to make a decision on how to transmit and/or engage with the brand message. The dual decision process might shed some light on how consumers engage with social media messages when motivated. We propose that consumers follow either a system 1 or system 2 process (Evans 2008; 2011; Kahneman 2011) when making a decision to engage. System 1 processing of content transmission is quick, unconscious, impulsive, intuitive, and reflexive. It is more likely that consumers engaged in a system 1 process will transmit content via a one-click social plugins (e.g., like). On the other hand, system 2 processing of content transmission is conscious, analytic, slow, and reflective. It is more likely that consumers engaged in a system 2 process will transmit content via composition-based social plugins which allow for a deeper mode of engagement (e.g., comments).

One objective in this research is to explore how consumers encode favorable social media messages. When do they use one-click social plugins such as likes, and when do they use deeper engaging composition-based social plugins such as comments? An overarching research question is:

> RQ: Depending upon message characteristics, which modes of transmission are more likely to be used by consumers when they are considering products versus when they are considering services?

3.5 Hypotheses

3.5.1 Brand Strategy Approach

Several scholars have found that service companies (e.g. IBM, Geico, and Chase) use a corporate branding strategy approach (Burt and Sparks 2002; McDonald and de Chernatony 2001). This is not surprising as Aaker (2004) states that consumers can easily relate to the organization and service personnel (frontline service employees) through corporate brand names. The use of product brand names is less likely to be effective for services, whereas the use of product brand names is more likely to be effective for products (Aaker 2004). For example, the Clorox brand name is confined to cleaning products and is less likely to appeal to company's other products such as Glade and Britta. Aaker (2004) notes that both company and product brand names have their own specific advantages, and, based on a company's offerings, an appropriate branding strategy should be adopted. Brown et al. (2005) find that the greater the relationship between organization and self, the greater the likelihood that an individual will provide positive WOM. For services, the degree of overlap between company brand name and self is likely to be higher, whereas for products it is between product brand name and self (Brown et al. 2005; Aaker 2004). Consumers seek to express their unique identity, self-enhancement, and attachment with brands by sharing brand messages. These motivations become more salient when consumers decode service messages containing corporate brand names. When consumers who are considering a service, receive a service message containing corporate brand name, they are more likely to be motivated to spread WOM. Subsequently, they are likely to encode the service message by taking appropriate actions such as liking and/or commenting on the message itself, and thus sharing their opinions with their networks of friends. This phenomenon of encoding will be more pronounced for consumers who are considering using a product when the product message contains product brand names as the motivations to spread the message become more salient under product condition.

> H1a: The use of corporate brand names in social media messages is more effective for services than for products.
>
> H1b: The use of product brand names in social media messages is more effective for products than for services.

3.5.2 Message Appeals

The use of message appeals (functional and emotional) is one of the most widely studied variables in the advertising communication literature (Turley and Kelly 1997). There still exists some debate in the service advertising literature whether functional or emotional appeals are effective. Some scholars have found a higher usage and effectiveness of functional appeals for services advertising (Stafford and Day 1995; Stafford 2005); whereas others have advocated a higher usage and effectiveness of emotional appeals (Cutler and Javalgi 1993; Motimer 2008; Tripp 1997). Mortimer (2008) states that most of these discrepancies arise due to either classification of emotional and functional appeals or the use of different dependent variables (e.g., intentions, attitudes and behaviors). In this study, we capture actual behaviors of liking and commenting on messages which is likely to provide a better support for appeal effectiveness for services social media communications.

Shavit (1990; 1991) argues that message appeals should match the offering type (Johar and Sirgy 1991). Emotional appeals should be used for experiential hedonic offerings, and functional appeals should be used for technical utilitarian offerings. Services involve higher consumer contact and participation than products. As such, services are more experiential and personal. The SERQUAL scale explicitly defines these personal experiences (Parasuraman, Zeithaml, and Berry 1988).

The functional and emotional aspect of the message motivates the consumers to share the content. The functional aspect is related to motives of sharing and exchange of useful practical information, and the emotional aspect is related to motives of excitement, satisfaction, and a feel good factor (Lovett, Peres, and Schachar 2013). We propose that consumer motivations to share and exchange useful practical information are more salient for functional messages when considering using products. Conversely, consumer motivations to share emotions such as excitement, satisfaction, and feel good factor are more salient for emotional messages when considering using services. When consumers who considering using a service, receive a service message and decode emotional experience expressed in the message, they are more likely to be motivated to spread the WOM. Subsequently, they are likely to encode the service message by taking appropriate actions such as liking and/or commenting on the message itself, and thereby sharing their opinions with their networks of friends. This phenomenon of encoding will be more pronounced for consumers who consider using products when they decode functional appeals within product messages.

> H2a: The use of functional appeals in social media messages is more effective for products than for services.

> H2b: The use of emotional appeals in social media messages is more effective for services than for products.

3.5.3 Use of Vividness

Products are considered tangible since they can be seen and felt, and can be easily shown in the form of images and videos. Services, on the other hand, do not have this attribute. Although tangibility is important in services (Berry and Clark 1986) and services can be shown in the form of visualization (mental picture of service's benefits or qualities), association (extrinsic goods, person, event, place, or object to the actual service), physical representation (tangibles that are directly or peripheral parts of the service), or even through documentation (information such as figures and facts via text), research suggests that tangibilzation is less likely to be effective through the use of vividness (e.g. visualization, physical representation, and association). Research suggests that tangible cues are more likely to be effective in services through words than images (Stafford 1996; Clow, James, Kranenburg, and Berry 2009). On the other hand, for products the use of images or high vividness is likely to be a more effective persuasion channel than would be text in online advertisements (Ahn and Bailenson 2011).

Companies can upload images and videos when disseminating social media messages, and generally use this feature to show their offerings such as product images, product review videos, product launch images/videos, etc. We propose that the use of vividness (images/videos) is more effective in social media messages for products than for services.

Consumer motivations such as entertainment, useful practical information, interest and excitement become salient when consumers see the use of vividness (images/videos) in messages. We contend that these consumer motivations are more salient in vivid messages for products than for services. When consumers, who consider using a product, receive a product message containing images and/or videos in the message, they are more likely to be motivated to spread WOM. Subsequently, they encode the product message by taking appropriate actions such as liking and/or commenting on the message itself, thus sharing their opinions with their networks of friends. However, for consumers considering services, they are less likely to be motivated to spread the messages containing images and/or videos that try to tangibilize the service rendered.

> H3a: The use of images in social media messages is more effective for products than for services.
>
> H3b: The use of videos in social media messages is more effective for products than for services.

3.6 Method

3.6.1 Data

We examine Facebook, the largest and the most popular social media site today. Facebook now has over 1 billion active users with over 140 billion friend connections (Facebook 2013). Over 70% of Fortune-500 companies have at least one Facebook account (brand page) through which they actively interact with their fanbase (Barnes, Lescault, and Wright 2013). Companies use these brand pages to broadcast information (e.g., wall posts) in an official, public manner to people who choose to connect with them (fans) (Zaglia 2013).

Our data comprised of Fortune-500 Company's Facebook wall posts. We initially followed 303 Fortune-500 company's Facebook accounts (brand pages) based on the list provided by Barnes (2010). These accounts were tracked for the week of 9/29/11. This resulted in 1,467 unique company wall posts from 213 Facebook accounts that were active during this time period. The range in number of messages per account was from 1 to 34 (mean = 6.89 SD = 5.90).

3.6.2 Content Analysis

Two coders were recruited to code the social media messages. The coders went through rigorous training sessions to ensure that they understood the key concepts and the coding scheme (Refer to Appendix B for the coding scheme). In the training sessions, each coder coded over 60 messages for practice. The intercoder reliability was calculated on 100 messages from a subsample of a separate data set (Lothia, Donthu, and Hershberger 2003; Neuendorf 2002). This procedure ensured non-contamination of the original dataset. The intercoder reliability was calculated for all the message characteristics using Rust and Cooil's (1994) PRL index. All reliabilities were above 0.90 and the mean PRL was 0.97, indicating good intercoder reliability.

The data set was then divided into two equally sized sets and each coder coded one of the two non-overlapping sets. All message strategies were coded as 1 if present or 0 if absent. The coders also recorded the total number of message likes and message comments -- the dependent variables. Further, the coders recorded the message time – calculated as the time when the message was sent out to the time when the data was archived and fanbase size -- the total number of fans (page likes) for each company Facebook account. The variables message time and fanbase were used as the control variables in our model (Refer to Figure 3.2).

3.6.3 Descriptive Statistics

We classified services and products Facebook accounts based on SIC codes (www.naics.com). Our data comprised of 81 product accounts (38%) and 132 service accounts (62%) (Refer to Table 3.2). Product accounts had a lower mean number of message likes (472) and comments (39) than did service accounts, with a mean number of message likes and comments, of 495 and 71, respectively. However, the average fanbase size was higher for product accounts (1,350,736) than for service accounts (1,297,706). Product accounts had a higher percentage use of corporate brand names (39.7%) than did services accounts (25.8%). The use of product brand names (product = 26.1%; service = 24.0%), functional appeals (product = 15.9%; service = 17.9%), emotional appeals (product = 51.0%; service = 54.6%), images (product = 53.9%; service

= 52.9%), and videos (product = 7.6%; service = 7.1%) were quite similar across messages in product and service accounts.

3.6.4 Model

To test our hypotheses we ran a Multivariate Multilevel Poisson Regression Model using HLM software (Raudenbush and Bryk 2002) to compare the effectiveness of social media messages across products and services accounts. Hierarchical models have been adapted for use with such multivariate outcomes (Raudenbush, Rowan, and Kang 1991). The model is as follows:

Level-1 Model:

$$E(COUNT_{ijk}|\pi_{jk}) = \lambda_{ijk}$$
$$\log[\lambda_{ijk}] = \eta_{ijk}$$
$$\eta_{ijk} = \pi_{Ljk} \times (DLIKES)_{1jk} + \pi_{Cjk} \times (DCOMMENT)_{1jk}$$

Level-2 Model:

$$\pi_{Ljk} = \beta_{10k} + \beta_{11k} \times (CB_{jk}) + \beta_{12k} \times (PB_{jk}) + \beta_{13k} \times (FA_{k}) + \beta_{14k} \times (EA_{jk}) + \beta_{15k} \times (IM_{jk}) + \beta_{16k} \times (VD_{jk}) + \beta_{17k} \times (Tsqrt_{jk}) + r_{Ljk}$$

$$\pi_{Cjk} = \beta_{20k} + \beta_{21k} \times (CB_{jk}) + \beta_{22k} \times (PB_{jk}) + \beta_{23k} \times (FA_{jk}) + \beta_{24k} \times (EA_{jk}) + \beta_{25k} \times (IM_{jk}) + \beta_{26k} \times (VD_{jk}) + \beta_{27k} \times (Tsqrt_{jk}) + r_{Cjk}$$

Level-3 Model:

$$\beta_{10k} = \gamma_{100} + \gamma_{101}(SC_k) + \gamma_{102}(Lnfanbase_k) + u_{L0k}$$
$$\beta_{11k} = \gamma_{110} + \gamma_{111}(SC_k)$$
$$\beta_{12k} = \gamma_{120} + \gamma_{121}(SC_k)$$
$$\beta_{13k} = \gamma_{130} + \gamma_{131}(SC_k)$$
$$\beta_{14k} = \gamma_{140} + \gamma_{141}(Sc_k)$$
$$\beta_{15k} = \gamma_{150} + \gamma_{151}(SC_k)$$
$$\beta_{16k} = \gamma_{160} + \gamma_{161}(SC_k)$$
$$\beta_{17k} = \gamma_{170}$$

$$\beta_{20k} = \gamma_{200} + \gamma_{201}(SC_k) + \gamma_{202}(Lnfanbase_k) + u_{C0k}$$
$$\beta_{21k} = \gamma_{210} + \gamma_{211}(SC_k)$$

$$\beta_{22k} = \gamma_{220} + \gamma_{221}(SC_k)$$
$$\beta_{23k} = \gamma_{230} + \gamma_{231}(SC_k)$$
$$\beta_{24k} = \gamma_{240} + \gamma_{241}(SC_k)$$
$$\beta_{25k} = \gamma_{250} + \gamma_{251}(SC_k)$$
$$\beta_{26k} = \gamma_{260} + \gamma_{261}(SC_k)$$
$$\beta_{27k} = \gamma_{270}$$

$COUNT_{ijk}$ represents the number of likes and comments for message j at occasion i for account k; *DLIKES* is an indicator which takes a value of 1 when the count is for the message likes and 0 when it is for comments. Likewise, *DCOMMENT* is an indicator which takes a value of 1 when the count is for the number of comments and 0 when it is number of likes. λ_{ijk} represents the event rate and is equal to $COUNT_{ijk}$, number of likes and comments, as the exposure rate is held constant[1]. The variance of $COUNT_{ijk}$ equals the mean of message likes and comments respectively. η_{ijk} is the log of the event rate, λ_{ijk}. The level 1 dependent variables π_{Ljk} and π_{Cjk} become outcome variables at level 2. We assume that random errors (r_{Ljk} and r_{Cjk}) at level 2 are multivariate normally distributed, $r_{jk} \sim N(0, T_j)$, where T_j represents the variance-covariance for r_{jk} (Raudenbush and Bryk 2002). Tsqrt at level 2 represents the transformed (square root) message time. Furthermore, The level 2 variables βs become outcome variables at level 3. We assume that random errors (u_{L0k} and u_{C0k}) at level 3 are multivariate normally distributed, $u_k \sim N(0, T_k)$, where T_k represents the variance-covariance for u_k (Raudenbush and Bryk 2002). Lnfanbase at level 3 represents the transformed (natural log) fanbase added as control variable. Detailed below by hypotheses are the parameters that capture the interactions of interest in testing the hypotheses H1a-H3b:

[1] The model can also be run by including message time variable as an exposure rate.

H1a- γ_{111} (likes) and γ_{211} (comments) captures the interaction between corporate brand (CB) (coded 1 if corporate brand present, else zero) and service account (SC) (1=SC, 0=product account)

H1b- γ_{121} (likes) and γ_{221} (comments) captures the interaction between product brand (PB) (coded 1 if product brand present, else zero) and service account (SC) (1=SC, 0=product account)

H2a- γ_{131} (likes) and γ_{231} (comments) captures the interaction between functional appeals (FA) (coded 1 if functional appeals present, else zero) and service account (SC) (1=SC, 0=product account)

H2b- γ_{141} (likes) and γ_{241} (comments) captures the interaction between emotional appeals (EA) (coded 1 if emotional appeals present, else zero) and service account (SC) (1=SC, 0=product account)

H3a- γ_{151} (likes) and γ_{251} (comments) captures the interaction between use of images (IM) (coded 1 if images present, else zero) and service account (SC) (1=SC, 0=product account)

H3b- γ_{161} (likes) and γ_{261} (comments) captures the interaction between use of videos (VD) (coded 1 if videos present, else zero) and service account (SC) (1=SC, 0=product account)

3.6.5 Results

3.6.5.1 Baseline Analysis

We first ran an intercept only model. The dependency between message likes and comments was high (r = 0.64) justifying a multivariate approach. Next, we added the covariates message time and fanbase to the model which further explained, 1.57% and 82% of the variance in the likes intercept, and 1.43% and 82% of the variance in the comments intercept. Next, we added message characteristics to the model. The inclusion of these variables further explained an additional 1.6% of the variation in likes and 9.17% of the variation in comments. Finally, we added the accounts characteristics to the model and later did a multivariate testing for all the coefficients to answer the research question RQ. This involved testing whether each coefficient across the dependent measures, message likes and comments were different from each other. We constrained the coefficients to a single estimate for cases where the multivariate testing was non-significant.

3.6.5.2 Main Effects

To test the main effects of the various message strategies and the control variables, we ran the model first with message characteristics, fanbase, and message time. We report our results in Table 3.3. The multivariate testing suggests the difference in the intercept across message likes and comments was significant (β_{Likes} = 2.57, $\beta_{Comments}$ = 0.99; $\chi^2_{(1)}$= 226.16), suggesting that the messages on an average had a higher percentage of likes than comments. The multivariate test for the variable representing corporate brand name was significant ($\chi^2_{(1)}$= 13.52). The variable representing corporate brand name was positive but non-significant for message likes (β_{Likes} = 0.13; t = 1.62); however, for message comments, the variable was negative and significant at the 0.1 level ($\beta_{Comments}$ = -0.20; t = -1.89). The use of a corporate brand name in a message yielded a lower percentage of message comments than message likes. The multivariate testing across the coefficient representing product brand name was non-significant ($\chi^2_{(1)}$= 0.71) and hence the estimates were constrained to a single estimate for our two dependent measures, message likes and message comments. The main effect for the use of product brand name (for both likes and comments) was non-significant (β = 0.02; t = 0.25).

For the variable representing functional appeals, the multivariate testing was non-significant ($\chi^2_{(1)}$= 0.04) between message likes and message comments and hence the estimates were constrained to a single estimate. The main effect for the use of functional appeals (for both likes and comments) was non-significant (β = 0.05; t = 0.56). The multivariate test for the variable representing emotional appeals was significant ($\chi^2_{(1)}$= 7.43). The variable emotional appeals was positive and significant for both message likes (β_{Likes} = 0.24; t = 3.24) and message comments ($\beta_{Comments}$ = 0.47; t = 4.79). The use of emotional appeals yielded a higher percentage of message likes and comments; although, the effect was more pronounced for message comments.

The multivariate test for the variable representing images was significant ($\chi^2_{(1)}$= 51.98). The variable representing images was negative and non-significant for message likes (β_{Likes} = -0.07; t = -0.98), but was significant for message comments ($\beta_{Comments}$ = -0.67; t = -6.72). When images were used, the percentage of message comments was lower. The multivariate test for the variable representing videos was significant ($\chi^2_{(1)}$= 24.84). The variable representing videos was negative and non-significant for message likes (β_{Likes} = -0.02; t = -0.15); however, it was significant for message comments ($\beta_{Comments}$ = -0.77; t = -4.29). When videos were used, the percentage of message comments was lower.

Furthermore, the multivariate test for the variable representing fanbase was non-significant ($\chi^2_{(1)}$= 2.17). Therefore, it was constrained to a single estimate for message likes and comments. The pooled effect for the fanbase coefficient (for both likes and comments) was positive and significant (β = 0.66; t = 33.0); the larger the fanbase, the greater the number of likes and comments. The multivariate test for the variable representing message time was non-significant ($\chi^2_{(1)}$= 0.56) between message likes and comments and therefore was constrained. The pooled effect for the message time coefficient, (for both likes and comments), was positive and significant (β = 0.02; t =

5.0); suggesting that the longer the message time, the higher is the rate of message likes and comments.

3.6.5.3 Hypotheses Testing

To test our hypotheses, we added the variables representing service accounts and the interactions between service accounts and message characteristics. We report our results in Table 3.4. The multivariate test for the variable representing service accounts was significant between message likes and comments ($\chi^2_{(1)}$= 10.51). The variable representing service accounts was negative and non-significant for message likes (β_{Likes} = -0.03; t = -0.14), whereas it was positive and significant for message comments ($\beta_{Comments}$ = 0.69; t = 2.64). There was a higher percentage of message comments for service accounts than for product accounts.

The multivariate tests between message likes and comments for all the interaction terms were non-significant. This implies that there is no difference between the two dependent variables. Therefore, we constrained each interaction term to a single estimate across message likes and comments to test our hypotheses. We report the results of our hypotheses using a single pooled estimate in Table 3.4.

H1a states that the use of corporate brand names in social media messages is more effective for services than for products. H1a was supported as the effect of the interaction was positive and significant for both message likes and comments (β = 0.38; t = 2.38). H1b states that the use of product brand name in social media messages is more effective for products than for services. H1b was supported as the effect of the interaction was negative and significant for both message likes and comments (β = -0.49; t = -2.88). H2a states that the use of functional appeals in social media messages is more effective for products than for services. H2a was not supported as the effect of the interaction was non-significant for both message likes and comments (β = -0.24; t = -1.26). H2b states that the use of emotional appeals in social media messages is more effective for services than for products. H2b was not supported as the effect of the interaction was non-significant for both message likes and comments (β = -0.08; t = -0.53). H3a states that the use of images in social media messages is more effective for products than for services. H3a was supported as the effect of the interaction was negative and significant for both message likes and comments (β = -0.40; t = -2.50). H3b states that the use of videos in social media messages is more effective for products than for services. H3b was supported as the effect of the interaction was negative and significant for both message likes and comments at the 0.1 level (β = -0.52; t = -1.93).

We plotted the significant interactions for our effective measures, message likes and comments. Refer to Figures 3.3 and 3.4.

3.7 Conclusion and Implications

In this essay we examined *how* and *when* the social media communications get transmitted. To answer how, we focused on the two modes of transmissions that users use ubiquitously, “Likes” and “Comments.” To answer when we examined how offering characteristics, services versus products are likely to affect the social transmission of content. By analyzing 1,467 unique company wall posts from 213 Fortune-500 Facebook accounts we find that the choice of marketing strategies that motivates consumers to share content does impact social media effectiveness, and specifically WOM activity as measured by number of generated message likes and comments.

We find that the message comments are positively related to the message likes. We believe that consumers engaging with the social media messages influence each other (de Vries, Gensler, and Leeflang 2012). The higher number of message likes for a given social media message might raise interest in the message causing individuals to engage more by liking and/or commenting on the message. This phenomenon can be seen as a social contagion effect where user's engagement with the brand posts influences others to engage with it (Aral and Walker 2011; de Vries, Gensler, and Leeflang 2012; Trusov, Bucklin, and Pauwels 2009). Thus for effective social media communications, marketers have to choose appropriate message strategies to instigate social contagion effect among their brand posts (Berger 2013).

Our results indicate that overall consumers are more likely to like a message than to comment on it. This finding of a higher percentage of message likes than comments is consistent with the previous research (de Vries, Gensler, and Leeflang 2012). Indeed, consumers are more likely to use system 1 process during encoding social messages. We further find that using corporate brand names, videos, and images has a lower percentage of message comments than message likes. Consumers are less likely to comment or use system 2 processing when they decode corporate brand name, videos, and images in social media messages. Although, there was no significant effect of the use of corporate brand names, videos, and images on message likes, we believe that consumers are likely to use system 1 process when they decode them in social media messages. Indeed, consumers are reluctant to comment on messages containing corporate brand names, videos, and images (de Vries, Gensler, and Leeflang 2012).

Furthermore, we find that using emotional appeals in social media messages increased percentage of likes and comments. Using emotional appeals motivates consumers to share content (Berger and Milkman 2012). We also find that the use of emotional content had a higher percentage of message comments than message likes. Consumers are less likely to like or use system 1 processing when they decode emotional content in messages. Use of emotions creates deeper engagement motivating consumers to comment and share the content. To create deeper engagement, we recommend that marketers implement more emotional appeals in their brand posts. The higher the percentage of fanbase, the higher is the rate of liking and commenting. Our results indicate a high influence of fanbase on message likes and comments. Also, longer the message exposure the higher is the rate of liking and commenting. Both fanbase and the exposure of messages influence the number of the message likes and comments. This suggests that the social media engagement can be enhanced by increasing the fans/followers as well as keeping the message active for longer time period. Indeed, exposing the brand posts for longer time and to a broader audience increases engagement (Berger 2013).

Marketing services is challenging and given the importance of WOM it becomes critical to understand the effective social media communications when offering services. We find that services messages had a higher percentage of comments than product messages. Given the complex nature of services, the consumers are more likely to use system 2 processing when decoding service messages thus we see high interpersonal communications in the form of comments. The higher percentage of comments for services messages might serve as a channel to reduce associated risks and to establish expectations for the services offered to the consumers.

We find that using corporate brand names in service social media messages is effective in generating a higher percentage of likes and comments than product social media messages. Indeed, the consumers of services relate to the corporate brand names and are more likely to be motivated to share the brand messages. On the other hand the motivation to share content for products becomes more salient when consumers decode and relate to the product brand names in social media messages offering products. Given the brand affinity between the brand name and the self, consumers are likely to express their unique identity, self-enhancement, and attachment with brands by liking and commenting on the messages (Lovett, Peres, and Schachar 2013). Indeed, marketers have to use appropriate branding strategies to motivate their consumers to share positive WOM through brand posts.

We further find that the use of vividness such as images and videos in social media messages is more effective for products than for services. Services are difficult to tangibilize through vividness (Stafford 1996) as they are intangible and heterogeneous compared to products. Products can be easily shown through images and video demonstrations. When consumers decode vividness in social media messages offering products, motivations to express interest and excitement, useful practical information and entertainment are likely to be more salient stimulating consumers to share content. Besides, using images and videos in an online environment to advertise products has been found to be an effective persuasive strategy (Ahn and Bailenson 2011). We recommend that marketers use more vividness when advertising products whereas refrain from using images and videos when advertising services.

The use of message appeals, functional and emotional, did not suggest any differential advantage for product and service social media messages. One possible explanation for the non-significant message appeals effect would be due to the differences within services category, namely experiential services and utilitarian services. Prior research suggests that message appeals should match the offering characteristics (Johar and Shirgy 1991). Emotional appeals should be used for experiential hedonic offerings whereas functional appeals should be used for technical utilitarian offerings. Albers-Miller and Stafford (1999) found that experiential services advertisements use more emotional appeals whereas utilitarian services advertisements use more functional appeals. We suggest that message appeals when matched with experiential and utilitarian offerings are likely to motivate the consumers to share the content and spread the WOM. For instance, consumers are more likely to share useful practical information (functional appeals) when considering utilitarian offerings. Motivations such as excitement, satisfaction, and a feel good factor are likely to be salient allowing consumers to share content when considering experiential offerings.

3.8 Limitations and Future Research

This research has several limitations that provide useful opportunities for future research. The first is the nature of the sample. Our data set comprised of Facebook posts from Fortune-500 companies that were active at a time period of one week. Thus our analysis did not track the changing behaviors (if any) over time. Moreover, using Facebook wall posts might limit our generalizability to other social media sites. Although our dataset was sufficient in running the empirical analysis to test our hypotheses we view them as potential limitations.

Second, our dataset did not come from controlled experiments which diminished our capability to capture characteristics of individuals who liked and commented on messages. Indeed, understanding individual consumer's reaction will better our understanding of the social media phenomena. This limitation could be overcome by conducting controlled and/or field experiments.

Third, there exist additional message strategies that marketers are likely to implement in their social media executions which were not investigated in our study (e.g., incentives, humor, interactivity, emotions, and links and cues for information search) (Berger and Milkman 2012; Schulze, Schöler, and Skiera 2014). We view this omission as a tradeoff and suggest future research to investigate them further.

Fourth, future research may want to extend this research to look at other social media sites such as Twitter, Linkedin, and Google+. Indeed, extending this research by exploring the effective message strategies for specific industries or product/service type will be useful.

Fifth, our results did not indicate any significant effect for message appeals between product and services messages. We recommend exploring this discrepancy by further characterizing the services and products into utilitarian and experiential offerings (Alexandrov, Lilly, and Babakus 2013). Match theory (Johar and Sirgy 1991) would be helpful in exploring effective message appeals.

Sixth, an interesting topic for further research would be to conduct a linguist analysis and test effective message styles across products and services. Such work has recently started to emerge in the marketing literature (Ludwig, de Ruyter, Friedman, Brüggen, Wetzels, and Pfann 2013). How do linguistic styles impact sharing behaviors? This will be an important research avenue.

Seventh, our data set comprised of one week and hence could not capture the changing trends in the effective communication strategies across products and services. It would be interesting to investigate the changing trends of usage and effectiveness of social media communications, if any, across products and services (Yadav and Pavlou 2014).

Eight, we explored two modes of communication “Likes” and “Comments” on Facebook. Exploring other such modes of communication on various social media sites such as retweeting, +1, and sharing will extend our understanding on how users share content on social media sites.

In conclusion, this research investigates the much important topic on effective social media communication strategies for services. In the process, we further investigate the modes of communication to share content on social media sites. Future research should further our effort in exploring the effective social media communication strategies across different markets and categories.

Table 3.1
Comparison of Previous Empirical Research on the Effective WOM Marketing Communications

	Content Type	WOM Measurement	Moderators	Modes of Transmission	Statistical Methodology	Key Findings
Mangold, Miller, and Brockway (1999)	Survey	None	None	None	Descriptive	Three content categories: quality, price, and value
Phelps, Lewis, Mobilio, Peery, and Raman (2004)	Email content	Direct - Forwarded emails	None	One	Descriptive	Strong emotions such as humor, fear, sadness or inspirations are to be forwarded more
Porter and Golan (2006)	TV ads	None	None	None	Descriptive	viral advertising relies on provocative content
Chiu, Hseih, Kao, and Lee (2007)	Email content	Inferred from consumer self-report	None	One	Regression	Utilitarian and hedonic messages get forwarded
Dobele, Lindgreen, Beverland, Vanhamme, and Wijk (2007)	Viral marketing campaign	None	Yes, gender	None	Descriptive	Surprise and emotions both trigger transmission of content thus making it viral. Disgust and fear based messages to be transmitted more by men than women
Berger (2011)	News articles	Direct-Forwarded emails and inferred from consumer self-report	None	One	ANOVA and Chi-square	Psychological state boosts sharing
Berger and Schwartz (2011)	Face-to-Face WOM	Direct - number of conversations	Yes, product characteristics (interesting, cues, and public visibility)	One	Multilevel Poisson Model	More interesting products get more immediate WOM but, contrary to intuition, do not receive more ongoing WOM over multiple months or overall. In contrast, products that are cued more by the environment or are more publicly visible receive more WOM both right away and over time.

Smith, Fischer and Yongjian (2012)	Twitter, Facebook, and YouTube	None	None	None	Poisson and Log-linear regression	Differences in the brand related UGC between Twitter, YouTube, and Facebook
de Vries, Gensler, and Leeflang (2012)	Facebook wallposts - 11 brands	Direct - message likes and comments	None	Two - Analyzed independently	Univariate Poisson regression	Vivid and interactive brand posts can increase likes. Interactive posts (questions) can boost comments
Jose-Cabezudo and Camarero-Izquierdo (2012)	Survey	Inferred from consumer self-report	None	One	SEM	Messages containing jokes, fun messages, chain messages and advertising are forwarded more.
Berger and Milkman (2012)	New York Times articles	Direct - Top email list and inferred from consumer self-report	None	One	Logistic regression	Content that evokes high emotional arousal (positive or negative) is more viral
Chen and Berger (2013)	News articles	Direct - number of conversations and inferred from consumer self-report	Yes, identity disclosure and conversation partner	One	Poisson, Log Models and ANOVA	Moderate controversy is likely to create more conversations. This effect is enhanced when individual's identity is not disclosed and also when the conversation takes place with a friend.
This research	*Facebook wallposts - Fortune 500*	*Direct - Message likes and comments*	*Yes, offering type (product versus service)*	*Two - Analyzed simultaneously*	*Multivariate Multilevel Poisson Regression*	*The use of corporate brand names, images, and videos had a lower percentage of comments whereas the use of emotional appeals had a higher percentage of both likes and comments. The use of corporate brand names is more effective for services messages whereas the use of images, videos, and product brand names is more effective for product messages.*

Note - The italicized text denotes the contributions of the paper.

Table 3.2
Message Characteristics (Level 1) and Facebook Account Type (Level 2)

Message Characteristics	Product	Services	Percentage of Messages	
			Product	Services
Corporate Brand Name	187	257	39.7%	25.8%
Product Brand Name	123	239	26.1%	24.0%
Functional Appeals	75	178	15.9%	17.9%
Emotional Appeals	240	544	51.0%	54.6%
Images	254	469	53.9%	52.9%
Videos	36	71	7.6%	7.1%
Mean Message Likes*	472	495		
Mean Message Comments*	39	71		
Facebook Account Type				
Facebook Accounts	81	132		
Mean Fanbase*	1,350,736	1,297,706		

*Rounded to nearest 1

Table 3.3
Multivariate Multilevel Poisson Model Results – Main Effects

	Likes			Comments				
	Effect	**SE**	**T**	**Effect**	**SE**	**t**	**Constrained to Pooled Estimate (SE)***	**Multivariate Testing $\chi^2_{(1)}$**
Intercept	2.57	0.1	25.58	0.99	0.12	8.03	NA	226.16
Main Effects								
Corporate Brand Name (1=yes)	0.13	0.08	1.62	-0.2	0.10	-1.89	NA	13.52
Product Brand Name (1=yes)	0.04	0.08	0.43	-0.04	0.11	-0.38	0.02 (0.08)	0.71
Functional Appeals (1=yes)	0.05	0.09	0.52	0.05	0.12	0.37	0.05 (0.09)	0.04
Emotional Appeal (1=yes)	0.24	0.07	3.24	0.47	0.09	4.79	NA	7.43
Images (1=yes)	-0.07	0.08	-0.98	-0.67	0.10	-6.72	NA	51.98
Videos (1=yes)	-0.02	0.13	-0.15	-0.77	0.18	-4.29	NA	24.84
Control Variables								
Facebook Fanbase	0.65	0.02	24.75	0.69	0.03	22.43	0.66 (0.02)	2.17
Message Time	0.02	0.01	4.11	0.02	0.01	3.80	0.02 (0.01)	0.56

* The coefficients were constrained to a pooled estimate when the multivariate tests were non-significant.

Table 3.4
Multivariate Multilevel Poisson Model Results – Hypotheses Testing

	Likes			Comments					
	Effect	**SE**	**T**	**Effect**	**SE**	**t**		**Constrained to Pooled Estimate (SE)***	**Multivariate Testing $\chi^2_{(1)}$**
Intercept	2.59	0.17	15.55	0.54	0.21	2.53		NA	122.73
Main Effects									
Corporate Brand Name (1=yes)	-0.1	0.13	-0.79	-0.51	0.18	-2.86		NA	6.95
Product Brand Name (1=yes)	0.32	0.14	2.3	0.44	0.18	2.37		0.34 (0.14)	0.56
Functional Appeals (1=yes)	0.19	0.16	1.19	0.37	0.22	1.67		0.23 (0.16)	0.97
Emotional Appeal (1=yes)	0.29	0.13	2.27	0.5	0.17	2.89		0.33 (0.12)	1.76
Images (1=yes)	0.17	0.13	1.27	-0.35	0.17	-1.97		NA	10.24
Videos (1=yes)	0.25	0.23	1.06	-0.21	0.32	-0.66		0.16 (0.23)	2.01
Service (1=yes)	-0.03	0.21	-0.14	0.69	0.26	2.64		NA	10.51
Moderating Effects									
Service × Corporate Brand Name	0.35	0.16	-2.16	0.48	0.22	-2.20	**H1a**	0.38 (0.16)	0.29
Service × Product Brand Name	-0.44	0.17	2.52	-0.68	0.23	3.01	**H1b**	-0.49 (0.17)	0.77
Service × Functional Appeal	-0.19	0.19	0.96	-0.46	0.27	1.70	H2a	-0.24 (0.19)	0.80
Service × Emotional Appeal	-0.08	0.16	0.49	-0.08	0.2	0.36	H2b	-0.08 (0.15)	0.01
Service × Images	-0.38	0.16	2.39	-0.48	0.21	2.26	**H3a**	-0.40 (0.16)	0.30
Service × Videos	-0.44	0.28	1.55	-0.85	0.39	2.19	**H3b**	-0.52 (0.27)	1.49
Control Variables									
Facebook Fanbase	0.66	0.03	25.22	0.69	0.03	22.42		0.67 (0.02)	1.53
Message Time	0.02	0.01	4.15	0.02	0.01	3.84		0.02 (0.01)	0.69

* The coefficients were constrained to a pooled estimate when the multivariate tests were non-significant. Supported Hypotheses are in bold.
Alternately we ran the model by including message time variable as an exposure rate. The results remained unchanged.

Figure 3.1
Social Media Communication Model

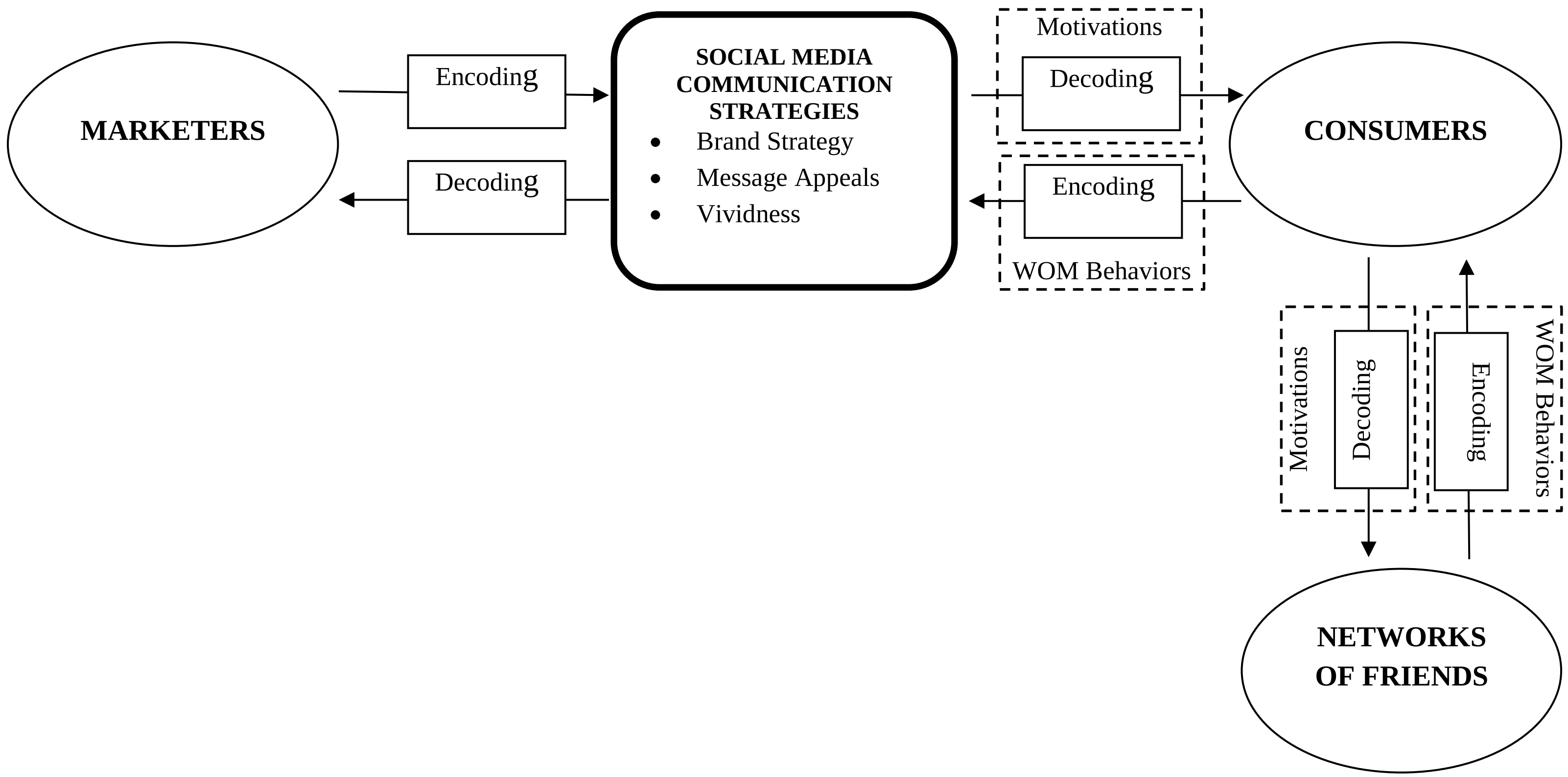
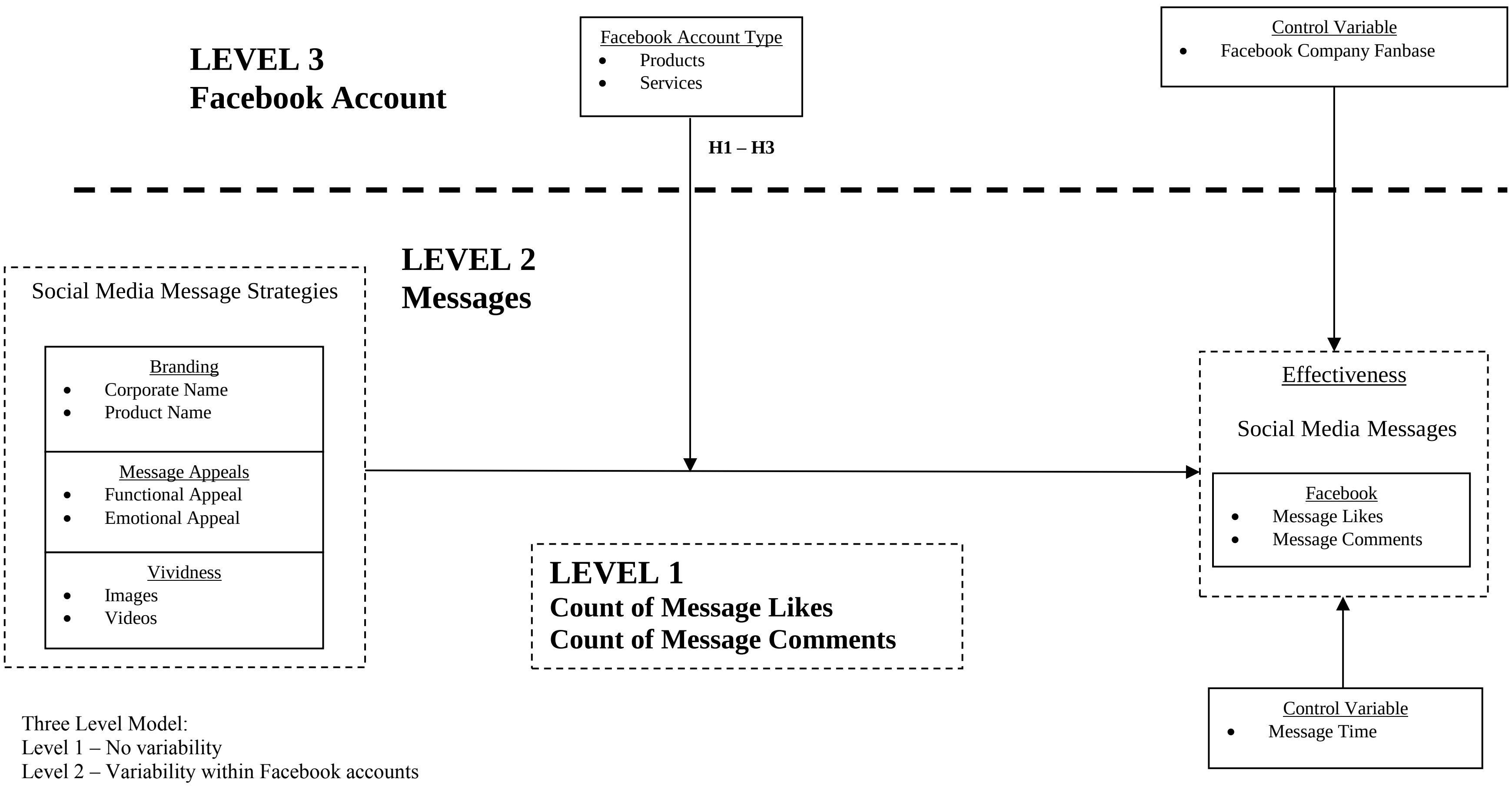


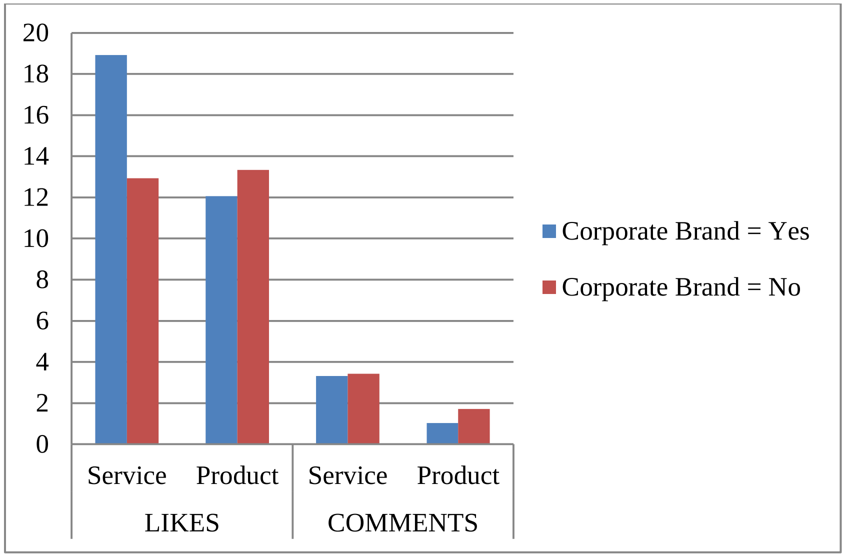
Figure 3.2
Empirical Model – Social Media Message Effectiveness



Three Level Model:
Level 1 – No variability
Level 2 – Variability within Facebook accounts
Level 3 – Variability across Facebook accounts

Figure 3.3
Interaction between Account Type and Brand Names for Message Likes and Comments

3.3a: Corporate Brand Name



3.3b: Product Brand Name

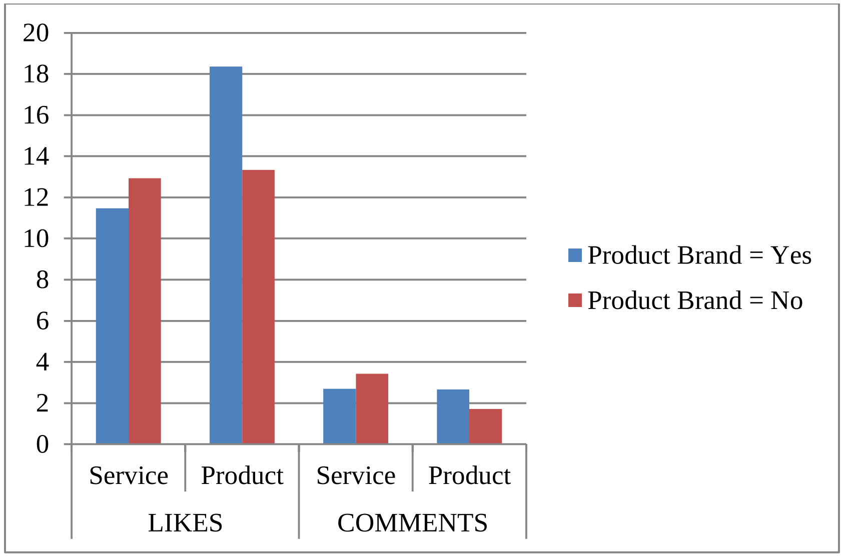
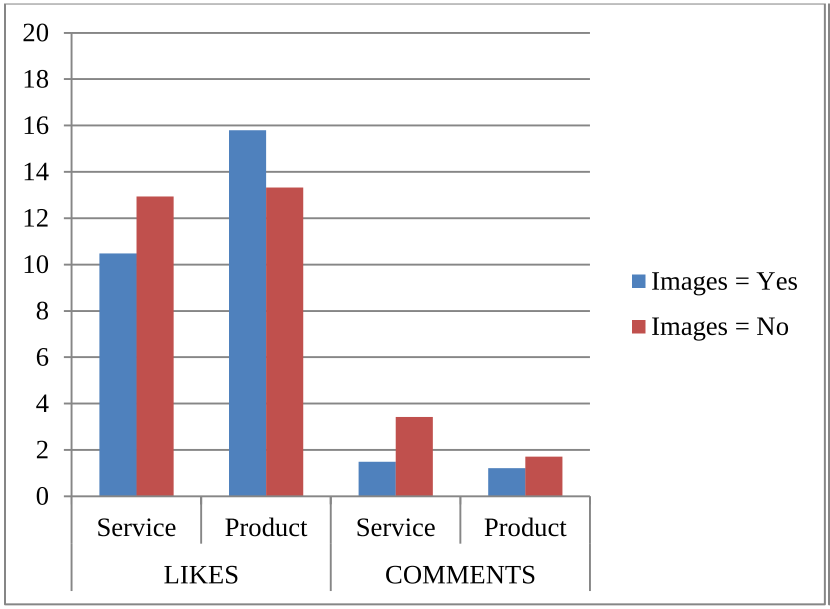
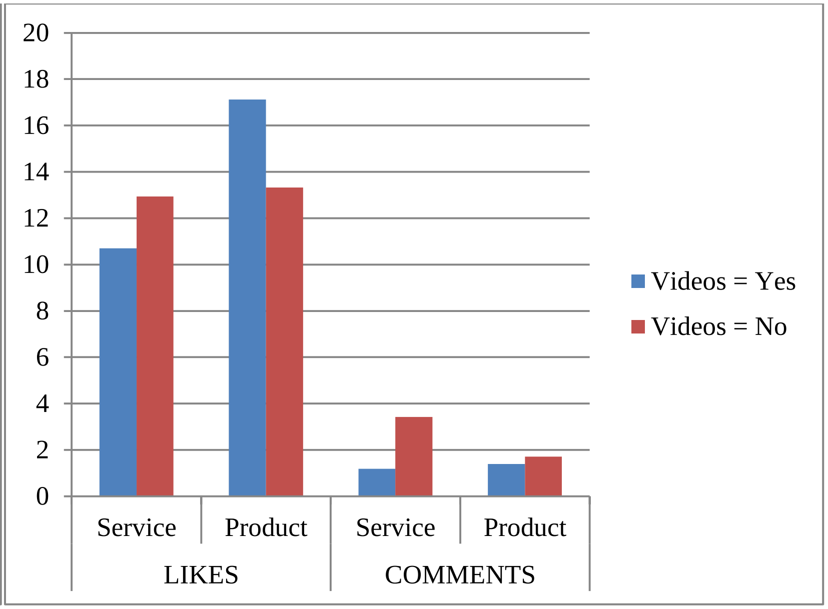


Figure 3.4
Interaction between Account Type and Vividness for Message Likes and Comments

3.4a: Images



3.4b: Videos



CHAPTER 4

CONCLUSION

Marketers are struggling with successful implementation of social media executions in their marketing efforts. Indeed, marketers on social media sites are always trying to determine what messages to post to get their followers engaged. The effectiveness of any social media site is derived when the followers read brand content, and is enhanced when they share it across their unique networks of friends that helps the brand – spread the word-of-mouth (WOM) (Berger and Milkman 2012; Berger 2013). Specifically, online WOM is particularly important for marketers as research suggests causal impact of WOM on sales, purchase intentions, product adoption, ROI, and brand awareness (Zhu and Zhang 2010; Chevalier and Mayzlin 2006; Godes and Mayzlin 2009; Liu 2006; Trusov, Buclin, and Pauwels 2009; Stephen and Galak 2012; Naylor, Lamberton and West 2012; Kumar and Mirchandani 2012).Thus, it is critical for marketers to implement appropriate social media message strategies that motivate followers to spread the WOM for their brands.

Literature on social media communications is beginning to emerge (Schulze, Schöler, and Skiera 2014). As such there is lack of guidance for marketers who are looking for effective ways to increase their user engagement (WOM) (Berger and Milkman 2012; de Vries, Gensler, and Leeflang 2012; Rapp et al. 2013). Furthermore, the existing literature has ignored some key moderators, market characteristics and offering type, as well as not fully explored the various new forms of communications that users use to spread the WOM in social media environments. Indeed, there is recognized priority by MSI (2012) for social media communications research.

This dissertation addresses these gaps by 1) investigating the usage and effectiveness of B2B social media communications, 2) identifying effective communication strategies when offering services versus products, and 3) fully exploring the two modes of social media message transmission that users use ubiquitously, message "Likes" and "Comments."

In essay one (chapter 2) we ask the question, whether differences exist in the business-to-business (B2B) and business-to-consumer (B2C) communication strategies in social media? Building on B2B advertising, organizational buying, and word-of-mouth theories, essay one highlights the key differences in B2B and B2C social media message strategies in terms of branding, message appeals, selling, and information search. Using 1,467 Fortune-500 Facebook company wall posts, we find differences in the usage and effectiveness (message likes and comments) of B2B and B2C social media practices. Specifically, the results indicate that the use of corporate brands, functional and emotional appeals, and information search had a higher percentage of message likes in B2B messages than in B2C messages. In addition, we find that B2B buyers, when compared to B2C consumers, have a higher message liking rate but a lower message commenting rate.

In essay two (chapter 3) we examine how and when the social media communications get transmitted. To answer how, we focus on the two modes of transmissions, message "Likes" and "Comments." To answer when, we examine how offering characteristics, products versus services are likely to affect the social transmission of content. We investigate the effectiveness of traditional advertising strategies in terms of brand strategies, message appeals, and the use of vividness in a social media environment by analyzing 1,467 Facebook message posts of Fortune-500 companies and measuring the number of message "Likes" and "Comments." We find that the use of corporate brand names is more effective for services messages whereas the use of images and videos as well as product brand names is more effective for product messages. Furthermore, the results indicate that the use of corporate brand names, images, and videos had a lower percentage of comments whereas the use of emotional appeals had a higher percentage of both likes and comments.

4.1 Theoretical Implications

This dissertation builds upon the communication theory to empirically test the social media communication effectiveness under different offerings and markets (Yadav and Pavlou 2014). This is the first study to incorporate the communication theory and fully test it in an interactive environment such as social media. This dissertation provides theoretical contributions by providing insights on how and when customers and their networks of friends transmit content in social media environments.

Essay one (chapter 2) addresses the relevant differences that exist between the B2B and B2C social media environments. Essay one contributes to the B2B advertising, organizational buying, and WOM literatures by empirically testing the differences (practices and effectiveness) in the B2B and B2C social media executions. Essay one is the first empirical study to explore the B2B and B2C social media practices of Fortune-500 companies and to test their effectiveness through various modes of diffusion, message likes and comments. This research deepens our understanding of the message strategies that actually influence online B2B word-of-mouth (WOM) popularity and effectiveness (de Vries, Gensler, and Leeflang 2012; Berger and Milkman 2012; Berger 2013). In addition essay one tests the effectiveness of B2B social media messages by measuring the number of likes and comments, two modes of transmission that users use ubiquitously. This analysis of how buyers and consumers transmit content furthers our understanding of WOM behaviors on social media for the two domains, B2B and B2C.

In essay two (chapter 3) we focus on how the key moderator of products versus services influence the various message strategies. This essay contributes to the WOM, service advertising, and social media literatures by empirically testing the differences in effectiveness of social media messages when offerings vary from products to services. Furthermore, this is the first study to fully explore the social media practices of Fortune-500 companies when offerings vary from products to services as well as their effectiveness through various modes of diffusion, message likes and comments. Given the importance of WOM in services (Bansal and Voyer 2000; Sweeney, Soutar, and Mazzarol 2012), essay two identifies important WOM communications to implement when offering services on social media to consumers.

4.2 Methodological Contribution

This dissertation provides a novel technique for observing social media effectiveness – online WOM, separate from the survey-dominated research used for the most part (Godes and Mayzlin 2009; Hofacker 2012; Yadav and Pavlou 2014). In essay one (chapter 2), we use content analysis to investigate the social media executions across B2B and B2C. Furthermore, we test the effectiveness of social media communication using Bayesian Analysis that helps explore the number of likes and comments for various message strategies.

In essay two, we introduce and estimate a Multivariate Multilevel Poisson Regression Model which allows us to test the effectiveness of social media messages across services and products Facebook company accounts and further test the differences across our dependent measures, message likes and comments. This methodology can be extended to other hierarchical data structures having multiple dependent measures (Raudenbush and Bryk 2002). Our methodology can inform both academics and managers who are interested in observing social media effectiveness through transmission of content (Yadav and Pavlou 2014).

4.3 Managerial Implications

Marketers have started to invest in social media to increase their brand awareness and loyalty, generate leads and increase sales, and build customer relationships (Kumar and Mirchandani 2012; Michaelidou, Siamagka, and Christodoulides 2011; Rapp et al. 2013). One way for marketers to fulfill such goals is to create brand communities on social media sites where the followers/fans can engage with the marketing communications (de Vries, Gensler, Leeflang 2012). This research provides direct applicable guidelines to marketers who are responsible for social media communications. The results of this research reveal the most likely effective marketing strategies that marketers should use when the offerings vary from products to services. Furthermore, this research provides guidance to the B2B marketers on how to improve their engagement among the buyers. In addition, our research also explores the two modes of communication that users on social media environments use to spread the WOM. Our results will be helpful to marketers who would like to increase the user engagement through either “Likes”, “Comments” or both. Indeed, our results can guide marketers who intent to implement social media in their IMC strategies.

Based on our results we recommend that B2B marketers use corporate brands, functional and emotional appeals, and information search cues and links in their social media communications. Furthermore B2B marketers should refrain from the use of direct calls to purchase and product brand names in their communications to their social media followers. We recommend marketers offering services to use corporate brand names but refrain from the use of product brand names, images and videos in their social media communications.

Furthermore, our results suggest that the fanbase and the exposure of messages influence the rate of message likes and comments. We recommend that marketers focus on increasing the fans/followers as well as keeping the messages active for longer time period to increase brand engagement.

4.4 Limitations and Future Research

This dissertation has some limitations that might provide useful opportunities for future research. First, this dissertation looks at a limited set of social media communication strategies in terms of brand strategy, message appeals, selling strategies, information opportunities, and the use of vividness. The models we tested were already complex and inclusion of other message strategies would have been challenging methodologically as well as theoretically. We view this omission as a limitation. Future research should explore and test other message strategies such as implementation of humor, sentiments, and interactivity in social media communications.

Second, this research explored two key moderators based on market characteristics and offering type. Our goal was to investigate effective strategies for B2B (chapter 2) and services (chapter 3). Indeed, exclusion of other moderators such as utilitarian/hedonic offerings (Schulze, Schöler, and Skiera 2014) and role of user involvement is a tradeoff. Future research should extend this research and investigate other moderators that are likely to affect the execution of social media messages. Research might investigate how the level of user involvement and offering characteristics (utilitarian/hedonic) affects the social media message effectiveness.

Third, our data comprised of Facebook wall posts from Fortune-500 companies and thus generalization of results to small businesses and other specific industries may not be applicable. This is a limitation in our research. Furthermore, our data was collected over one week which does not capture the changing trends over time. Our dataset was sufficient enough to run several types of models to test our hypotheses. However, exclusion of longitudinal analysis is a tradeoff in our research. Future research should investigate the use and effectiveness of social media communications for small businesses as well as specific industries such as retail, airlines, automobiles, and finance. Furthermore capturing and analyzing changing trends in the social media usage among businesses and customers will better our understanding of the phenomena (Yadav and Pvalou 2014).

Fourth, the dataset for this research did not come from a set of controlled experiments. Thus, our analysis was incapable of controlling various nuances at individual user level; a research limitation. This limitation could be overcome by conducting controlled and/or field experiments. It would be worthwhile to validate our findings in a controlled setting.

Fifth, our goal in this research was to capture the popularity of brands posts which we measured as number of likes and number of comments. We did not further categorize the valence of comments. This is a limitation in our research. As both positive and negative comments enhance interest in the brand posts (de Vries, Gensler, and Leeflang 2012), it would be interesting to analyze the effects of positive and negative comments on B2B and services brand post popularity for various message strategies investigated in this research.

In addition to addressing various limitations, our research findings provide at least seven worthwhile directions for future research. First, as different types of social media sites have their own unique architecture, culture and norms (Smith, Fischer, and Yongjian 2012) that are likely to affect the execution of social media message strategies, future research might investigate the effectiveness of social media executions across various social network sites such as LinkedIn, Twitter, Pinterest and Google+. Our findings can provide guidance to academics who intend to investigate communication strategies in various interactive media (e.g. mobile ads, banner ads, search ads, and online paid ads) as well as traditional outlets (e.g., print ads and TV commercials). Specifically, our findings can help academics identify appropriate IMC strategies that companies could implement when incorporating social media in their marketing efforts.

Second, it would be worthwhile to further our effort and explore the effective B2B and services social media strategies beyond ‘Likes’. Specifically, does liking messages/content help in improving marketing outcomes (e.g. brand loyalty, awareness, and equity) and financial outcomes (sales, stock price and generation of leads) in B2B as well as services contexts? Our findings of effective communication strategies might help academics to explore this question.

Third, our results could be useful in identifying key social media influencers (well-connected hubs) as well as in increasing the effect and value of social media influence of individuals who are prone to share brand messages sent out by marketers (Kumar and Mirchandani 2012). Marketers could target these influencers through various social media campaigns to derive brand related outcomes. Based on our results, we encourage academics to investigate the effectiveness of social media message strategies on brand influencers (seeding strategies).

Fourth, marketers can gain certain control on their brand communications on social media sites by exchanging messages with their customers. Thus in this research we investigated marketer’s communications to their customers. Future research can build on our conceptual framework to investigate social media communications between customers and their networks of friends as well as marketers’ responses to these communications (Yadav and Pavlou 2014). It will be interesting to investigate further how the meaning and value of these messages sent by marketers change as a result of customer interactions (Kozinets et al. 2010). Specifically, we explored the number of comments for various message strategies. It would be worthwhile to further explore the comments on messages sent by the companies. Marketers could use this information to improve their listening skills on what customers have to say about their brands, products and services. In addition, it could provide vital information on competition.

Fifth, we encourage academics to identify and test the salient psychological motivations that drive WOM among B2B buyers and consumers of services. Future research can build upon our findings and conduct experiments to validate our results as well as determine key psychological motivations driving the sharing of content.

Sixth, research might also investigate the effectiveness of valence of emotional appeals used in social media communications. Specifically, we encourage academics to investigate emotional content that provokes high psychological arousal in social media environments (Berger and Milkman 2012). In addition, research could look into how consumers share this content through various social plugins across different social media platforms.

Seventh, an interesting topic for future research would be to conduct a linguistic analysis to test the effective communication styles across products and services as well as B2B and B2C domains. This analysis will provide richer information on effective social media communications.

In conclusion, our objective in this research was to improve our understanding on the social media phenomena. In the process we identified and found differences in the effectiveness of message strategies across (1) B2B and B2C and (2) services and products. Furthermore we investigated the modes of transmission (message likes and comments) that users use to share content on social media sites. This research responds to the call for research into social media. Given scant research on this topic, we believe that our findings will encourage future research in exploring the social media phenomena.

APPENDIX A

LIST OF FORTUNE-500 COMPANIES

Company	Rank 2010	Revenue ($ million)	Industry
Walmart	1	408214.00	General Merchandisers
GE	4	156779.00	Diversified Financials
Conoco Philips	6	139515.00	Petroleum Refining
AT&T	7	123018.00	Telecommunications
Ford Motor Company	8	118308.00	Motor Vehicles and Parts
HP	10	114552.00	Computers, Office Equipment
Citi	12	108785.00	Commercial Banks
Verizon Wireless	13	107808.00	Telecommunications
General Motors	15	104589.00	Motor Vehicles and Parts
Wells Fargo	19	98636.00	Commercial Banks
Kroger	23	76733.20	Food and Drug Stores
Costco	25	71422.00	Specialty Retailers
The Home Depot	29	66176.00	Specialty Retailers: Other
Target	30	65357.00	General Merchandisers
Walgreens	32	63335.00	Food and Drug Stores
Johnson & Johnson Network	33	61897.00	Pharmaceuticals
State Farm Insurance	34	61479.60	Insurance: Property and Casualty (mutual)
Microsoft	36	58437.00	Computer Software
Dell	38	52902.00	Computers, Office Equipment
Pfizer	40	50009.00	Pharmaceuticals
Lowe's Home Improvement	42	47220.00	Specialty Retailers
Best Buy	45	45015.00	Specialty Retailers
The Dow Chemical Company	46	44945.00	Chemicals
SUPERVALU Pharmacies	47	44564.00	Food and Drug Stores
PepsiCo	50	43232.00	Food Consumer Products
Met Life	51	41098.00	Insurance: Life, Health (stock)
Safeway	52	40850.70	Food and Drug Stores
Kraft Foods	53	40386.00	Food Consumer Products
Cisco	58	36117.00	Network and Other Communications Eqpt.
FedEx	60	35497.00	Mail, Package, and Freight Delivery
Northop Grumman Corporation	61	35291.00	Aerospace and Defense
Aetna	63	34764.10	Health Care: Insurance and Managed Care
New York Life Insurance Company	64	34014.30	Insurance: Life, Health (mutual)
Walt Disney	65	38063.00	Entertainment
Sprint	67	32260.00	Telecommunications
Liberty Mutual	71	31094.00	Insurance: Property and Casualty (stock)
Coca-Cola	72	30990.00	Beverages

Time Warner	82	28842.00	Entertainment
Tyson Food Service	87	27165.00	Food Production
American Express	88	26730.00	Commercial Banks
Rite Aid	89	26289.50	Food and Drug Stores
TIAA-CREF	90	26278.00	Insurance: Life, Health (mutual)
Raytheon	95	24881.00	Aerospace and Defense
The Hartford	97	24701.00	Insurance: Property and Casualty (stock)
Travelers insurance	98	24680.00	Insurance: Property and Casualty (stock)
Amazon.com	100	24509.00	Internet Services and Retailing
Staples	101	24275.50	Specialty Retailers
Google	102	23650.60	Internet Services and Retailing
Macy's	103	23489.00	General Merchandisers
Oracle	105	23252.00	Computer Software
John Deere	107	23112.40	Construction and Farm Machinery
McDonald's	108	22744.70	Food Services
Motorola	110	22063.00	Network and Other Communications Eqpt.
Northwestern Mutual	115	21602.60	Insurance: Life, Health (mutual)
Nationwide Insurance	118	20751.00	Insurance: Property and Casualty (stock)
The TJX Companies	119	20288.40	Specialty Retailers
Nike	124	19176.10	Apparel
Alcoa	127	18745.00	Metals
Aflac Duck	130	18254.40	Insurance: Life, Health (stock)
USAA	132	17557.60	Insurance: Property and Casualty (stock)
JCPenney	133	17556.00	General Merchandisers
Kohl's	135	17178.00	General Merchandisers
Whirlpool	136	17099.00	Electronics, Electrical Equipment
Avnet	142	16229.90	Wholesalers: Electronics and Office Eqpt.
Manpower	143	16038.70	Temporary Help
Capital One	144	15980.10	Commercial Banks
Constellation NewEnergy	149	15598.80	Energy
Xerox	150	15179.00	Computers, Office Equipment
General Mills	155	14691.30	Food Consumer Products
Medtronic	160	14599.00	Medical Products and Equipment
Gap	162	14197.00	Specialty Retailers
Smithfield Foods	163	14190.50	Food Production
Union Pacific Railroad	164	14143.00	Railroads
Toys "R" Us	171	13568.00	Specialty Retailers
American Electric Power	172	13489.00	Energy
Chubb Insurance	176	13016.00	Insurance: Property and Casualty (stock)
ConAgra Foods, Inc.	178	12980.80	Food Consumer Products
Sara Lee Deli	180	12881.00	Food Consumer Products
Kellogg's	184	12575.00	Food Consumer Products

PPG Industries	190	12239.00	Chemicals
Office Depot	192	12144.50	Specialty Retailers
Eaton Corporation	194	11873.00	Industrial Machinery
Dollar General	195	11796.40	General Merchandisers
Waste Management	196	11791.00	Waste Management
Monsanto Company	197	11740.00	Chemicals
DISH Network	200	11664.20	Telecommunications
Navistar International Corporation	202	11569.00	Motor Vehicles and Parts
Science Applications international Corp	215	10847.00	Information Technology Services
Yum! Brands	216	10836.00	Food Services
Entergy	219	10745.70	Utilities: Gas and Electric
Textron Systems	220	10548.00	Aerospace and Defense
US Airways	222	10458.00	Airlines
Texas Instruments	223	10427.00	Semiconductors & Other Electronic Comp.
SunTrust	224	10420.00	Commercial Banks
QuALCOMM Incorporated	225	10416.00	Network and Other Communications Eqpt.
Land O' Lakes	226	10408.50	Food Consumer Products
Avon Product, Inc.	228	10382.80	Household and Personal Products
Southwest Airlines	229	10350.00	Airlines
Parker Hannifin	230	10309.00	Industrial Machinery
BJ's Wholesale Club	232	10187.00	Specialty Retailers
Thermo Fisher Scientific	234	10109.70	Scientific, Photographic, and Control Eqpt.
Progress Energy	239	9885.00	Utilities: Gas and Electric
Starbucks	241	9774.60	Food Services
Xcel Energy	244	9644.30	Utilities: Gas and Electric
First Data	250	9313.80	Financial Data Services
Pepco	251	9259.00	Utilities: Gas and Electric
GameStop	255	9078.00	Specialty Retailers
CSX	259	9041.00	Railroads
Principal Financial Group	266	8849.10	Insurance: Life, Health (stock)
eBay	267	8727.40	Internet Services and Retailing
Limited Brands	269	8632.50	Specialty Retailers
Nordstrom	270	8627.00	General Merchandisers
The Bank of New York Mellon	274	8345.00	Commercial Banks
Republic Services	278	8199.10	Waste Management
Whole Foods Market	284	8031.60	Food and Drug Stores
DTE Energy	285	8014.00	Utilities: Gas and Electric
Discover	286	7985.70	Commercial Banks
Norfolk Southern Corp	287	7969.00	Railroads
Chesapeake Energy	296	7701.90	Mining, Crude-Oil Production
Kodak	297	7606.00	Scientific, Photographic, and Control Eqpt.
Campbell's Kitchen	299	7586.00	Food Consumer Products
C.H. Robinson Worldwide, Inc.	301	7577.20	Transportation and Logistics

Quest Diagnostics Employer Solutions	303	7455.20	Health Care: Pharmacy and Other Services
Western Digital	304	7453.00	Computer Peripherals
Family Dollar	305	7400.60	General Merchandisers
Ball Corporation	307	7345.30	Packaging, Containers
Estee Lauder	308	7323.80	Household and Personal Products
Office Max	313	7212.10	Specialty Retailers
Bath & Body Works	314	7208.30	Specialty Retailers
Ross Dress for Less	316	7184.20	Specialty Retailers
Sherwin-Williams	319	7094.20	Chemicals
CarMax	323	7028.30	Automotive Retailing, Services
Dole	331	6782.70	Food Consumer Products
Charter Communications	332	6755.00	Telecommunications
Goodrich Corporation	334	6685.60	Aerospace and Defense
AGCO	337	6630.40	Construction and Farm Machinery
ACS	341	6523.20	Information Technology Services
Thrivant Financial for Lutherans	342	6514.80	Insurance: Life, Health (mutual)
Yahoo!	343	6460.30	Internet Services and Retailing
American Family Insurance	344	6453.40	Insurance: Property and Casualty (stock)
Dillard's Inc.	348	6226.60	General Merchandisers
Symantec	353	6149.90	Computer Software
Sallie Mae	354	6144.70	Diversified Financials
Interpublic Group	358	6027.60	Advertising, Marketing
Virgin Media	359	6013.60	Telecommunications
The McGraw - Hill Companies	363	5951.80	Publishing, Printing
Barnes & Noble	372	5596.30	Specialty Retailers
Newell Rubbermaid	373	5577.60	Home Equipment, Furnishings
Pitney Bowes	375	5569.20	Computers, Office Equipment
Dr Pepper Snapple Group	378	5531.00	Beverages
Weyerhaeuser	379	5528.00	Forest and Paper Products
CH2M HILL	381	5499.30	Engineering, Construction
Clorox	384	5450.00	Household and Personal Products
Northeast Utilities	385	5439.40	Utilities: Gas and Electric
Mattel	387	5430.80	Miscellaneous
Advance Auto Parts	389	5412.60	Specialty Retailers
Corning Incorporated	391	5395.00	Network and Other Communications Eqpt.
PetSmart	393	5336.40	Specialty Retailers
Hershey's	395	5298.70	Food Consumer Products
YRC Worldwide	396	5282.80	Trucking, Truck Leasing
Dollar Tree	397	5231.20	Specialty Retailers
Terex Corporation	402	5205.00	Construction and Farm Machinery
Amerigroup Corporation	404	5188.10	Health Care: Insurance and Managed Care
Mutual of Omaha Insurance	408	5149.60	Insurance: Life, Health (mutual)

Master Card	411	5098.70	Financial Data Services
Western Union	413	5083.60	Financial Data Services
Ralph Lauren	417	5018.90	Apparel
Anixter	422	4982.40	Wholesalers: Diversified
Century Link	423	4974.20	Telecommunications
Atmos Energy	424	4969.10	Utilities: Gas and Electric
Foot Locker	428	4854.00	Specialty Retailers
Harley-Davidson	430	4838.60	Miscellaneous
Black & Decker	435	4775.10	Home Equipment, Furnishings
Big Lots	436	4726.80	Specialty Retailers
Travel Centers of America	440	4699.80	Specialty Retailers
NYSE Euronext	444	4687.00	Securities
El Paso Corporation	447	4631.00	Pipelines
Unisys Corp	452	4597.70	Information Technology Services
Pepsi	464	4421.30	Beverages
Dick's Sporting Goods	466	4412.80	Specialty Retailers
Graybar	470	4377.90	Wholesalers: Diversified
Flowserve	473	4365.30	Industrial Machinery
Rockwell Automation	476	4332.50	Electronics, Electrical Equipment
Kindred Healthcare	477	4326.30	Health Care: Medical Facilities
Radio Shack	481	4276.00	Specialty Retailers
CA Technologies	482	4271.00	Computer Software
Erie Insurance	484	4255.40	Insurance: Property and Casualty (stock)
Sealed Air Corporation	487	4242.80	Packaging, Containers
Live Nation	490	4232.00	Entertainment
H&R Block	493	4213.40	Diversified Financials
Blockbuster	500	4161.80	Specialty Retailers

APPENDIX B

CODING SCHEME

Variable Name	Description
Communication Type (1= B2B, 2 = B2C, 3 = both)	B2B and B2C communications: The communication type will depend upon the type of the product/service marketed and also the intended audience.
Company Brand Name (1 = yes, 0 = no)	A social media message that has a company brand name mentioned in the message.
Product Brand Name (1 = yes, 0 = no)	A social media message that has a product brand name mentioned in the message.
Functional Appeal (1 = yes, 0 = no)	Functional appeal deals with specific product specification, feature, performance, and more. A functional based message would communicate only technicalities that are relevant to describe the product and/or a service or even a company.
Emotional Appeal (1 = yes, 0 = no)	Emotional appeal attempts to stir up either negative or positive emotions. Messages containing themes such as fear, humor, romance, sensuousness, adventure, guilt, play/contest, and other emotional cues.
Direct Calls to Purchase (1 = yes, 0 = no)	Direct calls to purchase refer to explicit statements encouraging prospective buyers to make an immediate purchase. For instance, these calls to action could be commands to make a purchase.
Information Search (1 = yes, 0 = no)	Links and cues that provide more information about the product, service and/or the company.
Images (1 = yes, 0 = no)	A social media message that has an image embedded within the message or contains a link to images.
Videos (1 = yes, 0 = no)	A social media message that has a video embedded within the message or contains a link to videos.

APPENDIX C

BAYESIAN CODE

Logistic Regression (Kruschke 2010)

```
Model  Logistic;
{
  for( i in 1 : n) {
              y[i] ~ dbern( mu[i] )
             mu[i] <- 1/(1+exp(-( beta[1] + beta[2]*x2[i] + beta[3]*x3[i] + beta[4]*x4[i] + beta[5]*x5[i] +
             beta[6]*x6[i] + beta[7]*x7[i])))
  }

#Priors
  for ( j in 1 : 7) { beta[j] ~ dnorm( 0.0,0.01)
  }
}
```

INITS

```
list(beta = c(0,0,0,0,0,0,0))
```

Bivariate Poisson (Ntzoufras 2011)

```
Model BivariatePoisson;
{
             for (i in 1:n) {miny[i]<-min( y1[i], y2[i]  ) }

      C<-0
             for (i in 1:n){
                          z3[i]~dpois(lambda[i,3]) I(0,miny[i]);
                          z1[i]<-y1[i]-z3[i];
                          z2[i]<-y2[i]-z3[i];
                          zeros[i] <- 0
                          zeros[i] ~ dpois( zeros.mean[i] )
                          zeros.mean[i] <-  -l[i] + C
                          l[i]<- -lambda[i,1]+z1[i]*log(lambda[i,1])-loggam(z1[i]+1) -
                          lambda[i,2]+z2[i]*log(lambda[i,2])-loggam(z2[i]+1);

             for (k in 1:3){
                          log( lambda[i,k] ) <- beta[k,1] + beta[k,2]*x2[i] + beta[k,3]*x3[i] + beta[k,4]*x4[i] +
                          beta[k,5]*x5[i] + beta[k,6]*x6[i] + beta[k,7]*x7[i]+beta[k,8]*x9[i] +beta[k,9]*x10[i] +
                          beta[k,10]*x1[i] + beta[k,11]*(x1[i]*x2[i]) + beta[k,12]*(x1[i]*x3[i]) +
                          beta[k,13]*(x1[i]*x4[i]) + beta[k,14]*(x1[i]*x5[i]) + beta[k,15]*(x1[i]*x6[i]) +
                          beta[k,16]*(x1[i]*x7[i])
   } }
#       Priors
             for (k in 1:3){ for (j in 1:16) { beta[k,j]~dnorm(0.0, 0.01) } }
}
```

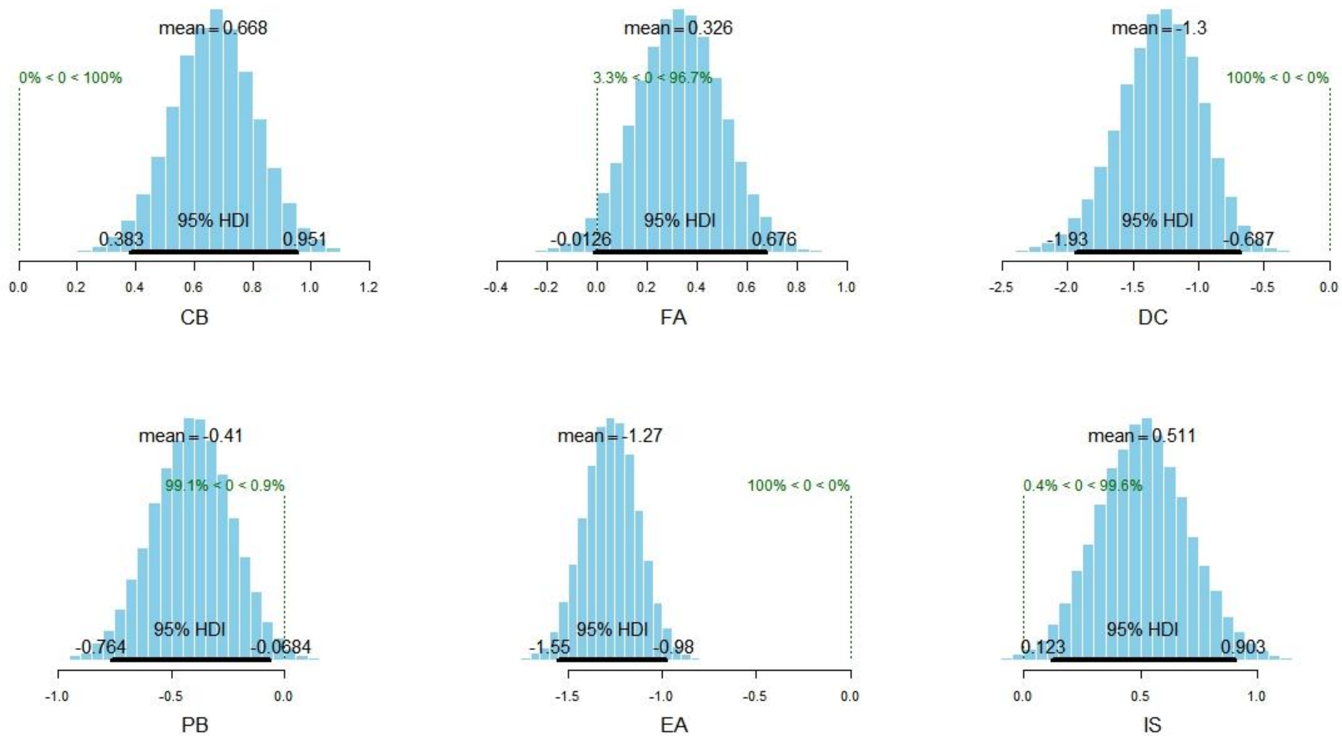
INITS

```
list(
beta =
structure(.Data=c(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
), .Dim = c(3, 16)),
z3=c(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0))
```

APPENDIX D

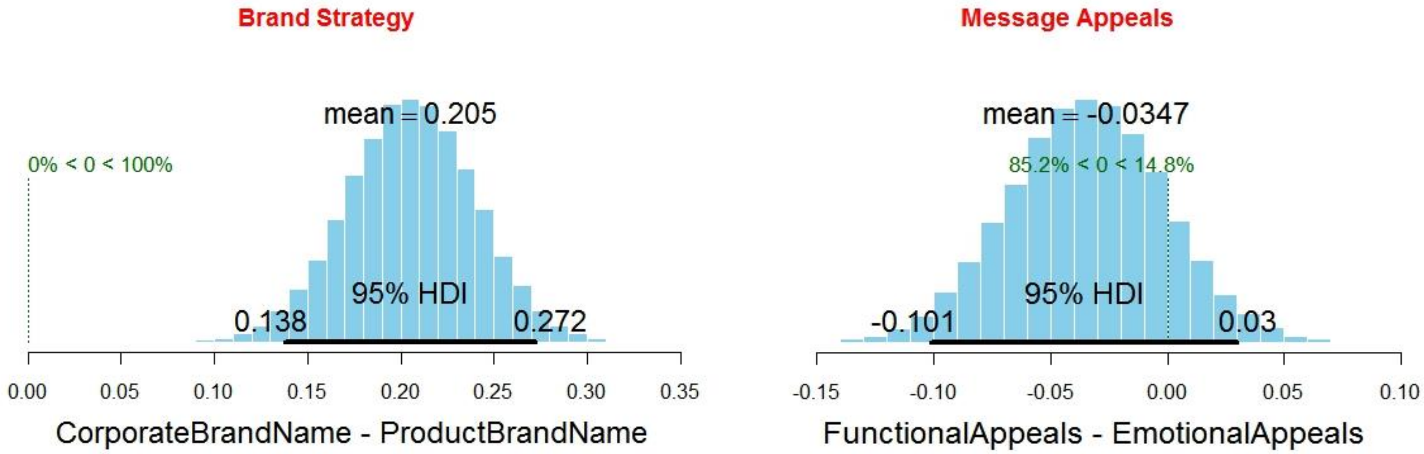
POSTERIOR PLOTS

Study 1 – Posterior Means – Logistic Regression (B2B)



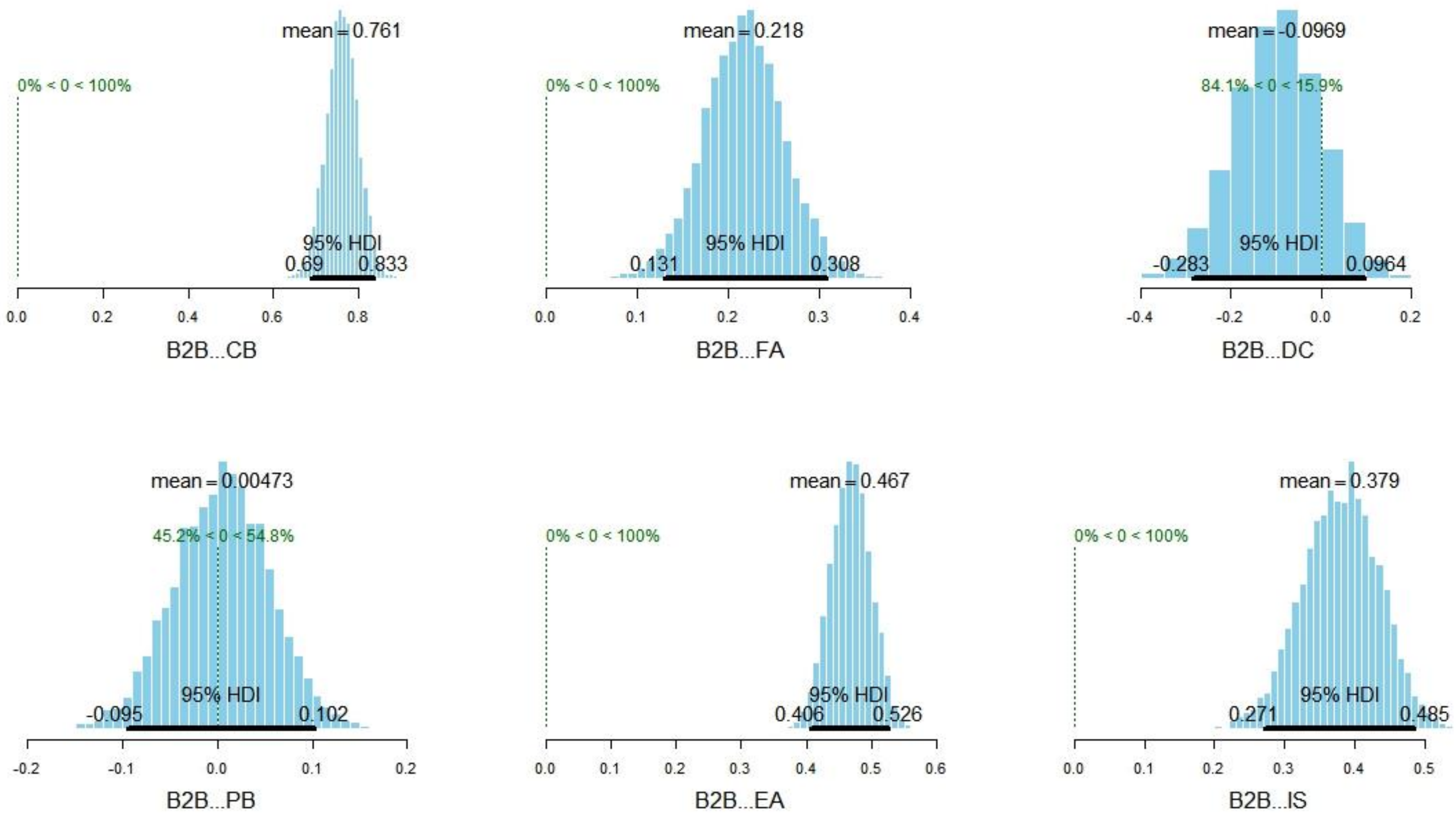
B2B = Business-to-Business; CB = Corporate Brand Name; PB = Product Brand Name; FA = Functional Appeals; EA = Emotional Appeals; DC = Direct Calls to Purchase; IS = Information Search.

Study 1 - Proportional Differences in Message Strategies within B2B Social Media Message



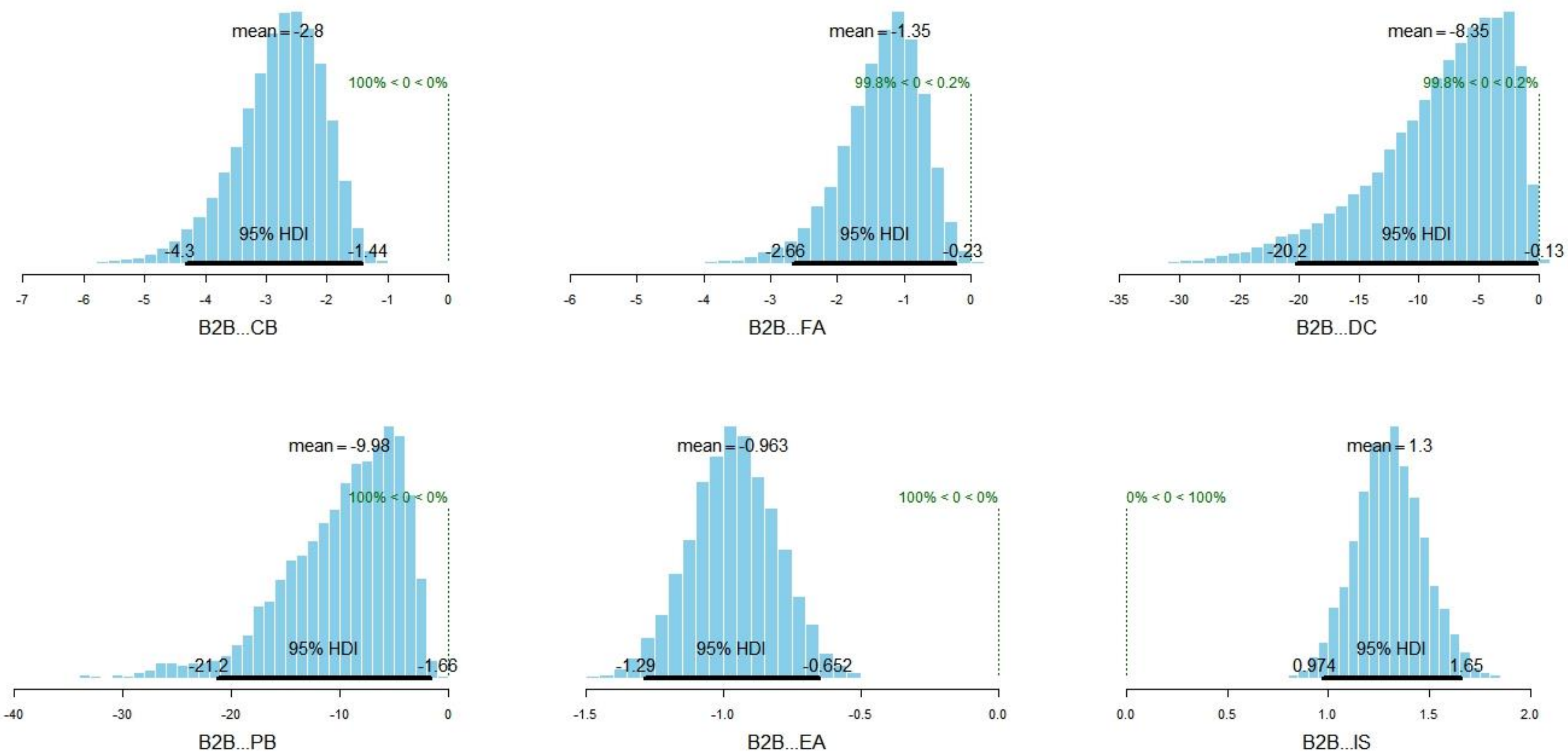
Note: The priors to test the proportional differences came from a beta distribution set as dbeta(10,10); mean = 0.5 with a moderate belief. The models were estimated using Gibbs sampler (MCMC) (Kruschke 2010) using 50,000 draws with a burn-in of 10,000.

Study 2 - Interaction Posteriors for Likes



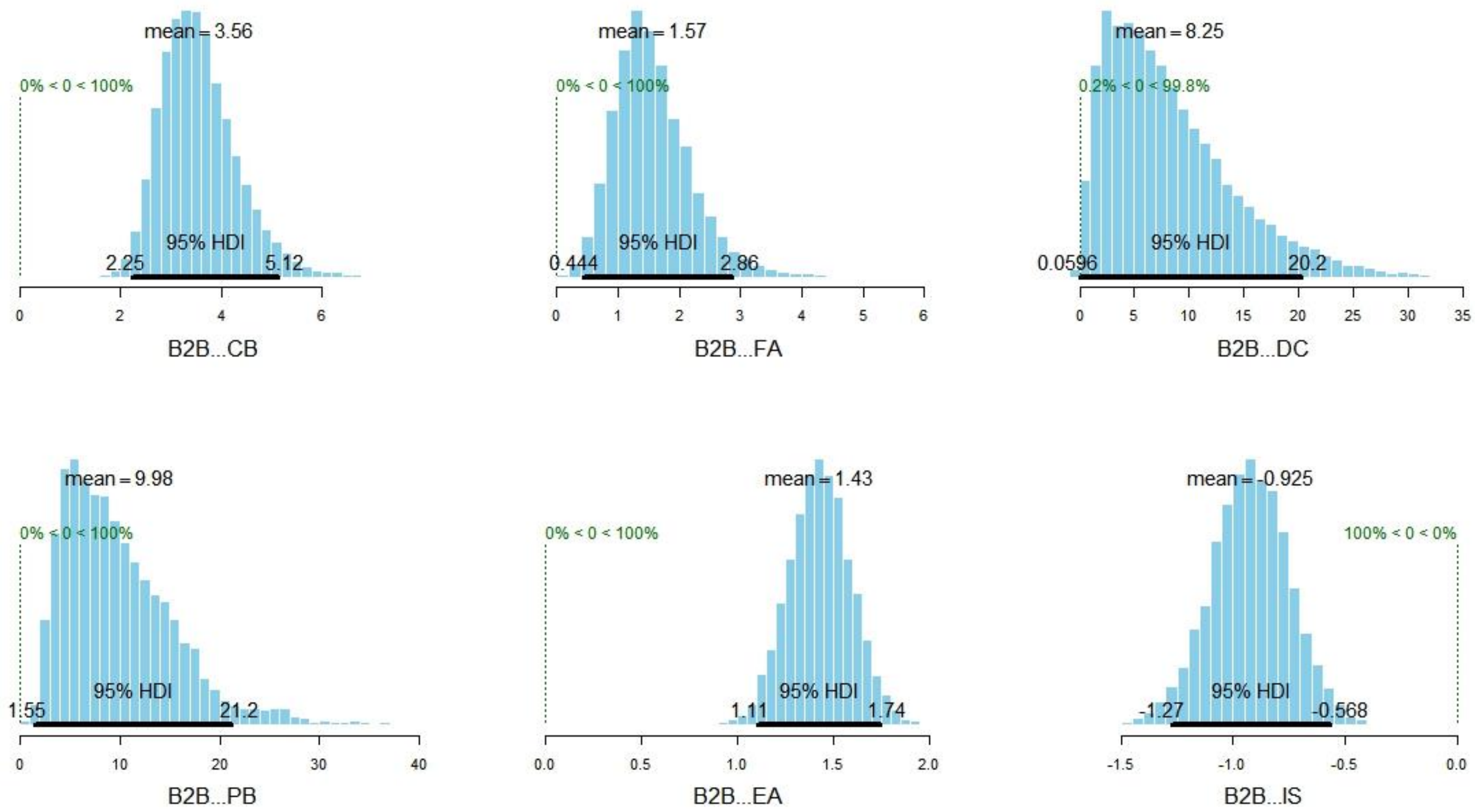
B2B = Business-to-Business; CB = Corporate Brand Name; PB = Product Brand Name; FA = Functional Appeals; EA = Emotional Appeals; DC = Direct Calls to Purchase; IS = Information Search.

Study 2 - Interaction Posteriors for Comments



B2B = Business-to-Business; CB = Corporate Brand Name; PB = Product Brand Name; FA = Functional Appeals; EA = Emotional Appeals; DC = Direct Calls to Purchase; IS = Information Search.

Study 2 - Interaction Posteriors – Difference Between Likes and Comments



Note – The posterior distribution differences were plotted by subtracting the 40,000 draws from likes and comments for each interaction variable.
B2B = Business-to-Business; CB = Corporate Brand Name; PB = Product Brand Name; FA = Functional Appeals; EA = Emotional Appeals; DC = Direct Calls to Purchase; IS = Information Search.

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