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Essays on Performance Implications of Social Media for Established and Nascent Firms

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Essays on Performance Implications of Social Media for Established and Nascent Firms

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Abstract

The possibility of large-scale communication with stakeholders brought about by social media has made these new channels of communication an important arena for spending marketing budgets. Despite the increasing share of social media in firms' marketing budget, there is significant heterogeneity in firms' social media communication practices even within the same venue and among firms from the same industry. As such, there is need for more research on how firms can leverage social media to achieve better performance. In order to address this broad question, two essays have been designed and executed.

The first essay utilizes integrated marketing communication as the theoretical lens to explores the implications of a unique opportunity offered by social media, that is, the ability to simultaneously broadcast to the mass audience (impersonal communication) and interact with individuals (personalized communication). Using a unique dataset, which includes the tweets, as well as financial data of S&P 500 firms present on Twitter, this essay reveals that the effects of communication modes are more intricate than a sole focus on the main effects would suggest.

Complementing the first essay which focuses on established firms, the second essay explores the implications of social media communication for B2B new ventures. Building on the literature on strategic similarity and dissimilarity, and comparative linguistics, this essay demonstrates that the lingual similarity of a B2B new venture's social media communications to those of its competitors and customers, can signal important information about the venture's marketing capabilities, thus impacting its success in fundraising.

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CHAPTER 1

1.1. Introduction

Marketers have long been tasked with improving firm performance through communications with stakeholders. The emergence of the Internet, and consequently social media, have dramatically changed the communication landscape, and as a result, this crucial task. Social media has offered marketers the unique opportunity to better influence their audience, through not only mass communication, but more importantly, one-on-one dialog.

As social media explodes in popularity, companies are increasingly investing in them, in order to capitalize on their financial value (Luo, Zhang, and Duan, 2013). According to a recent survey, the social media marketing's share of firms' total marketing budget is projected to increase from 10.5% in 2017 to about 18.5% in 2022 (CMO Survey 2017). Despite the surge in social media marketing budget, firms are still experimenting with their use of social media (Gong et al. 2017), and there is significant heterogeneity in firms' social media communication practices even within the same venue (e.g. Twitter) and among firms from the same industry. For example, Hewett et al. (2016) observe that Bank of America uses Twitter mainly for customer service and personalized communication, while other banks in their study (e.g. Wells Fargo) mainly use Twitter as a means for impersonal communication (i.e., broadcasting and promotional activities). Similarly, firms differ in terms of the lingual aspects of their social media communication: while some firms follow the communication norms constructed by their industry (Swani, Brown, and Milne, 2014), others follow lingual patterns that are distinct from their potential competitors.

There is no surprise, then, that firms vary widely in terms of the effectiveness of their social media presence. For example, Hewett et al. (2016) find notable differences in the effectiveness of Twitter communication across major banks. Specifically, they find that the quantity of tweets by Bank of America positively impacts customer deposits, but this is not the case for other banks (e.g. Wells Fargo). As another example, although ING-Diba, a European bank, was able to proficiently quiet a social media firestorm caused by one of their TV commercials (Pfeffer, Zorbach, and Carley 2014) through employing a positive tone and keeping themselves out of endless debates, United Airlines has been, in many cases of service failure, unsuccessful in properly managing social media communication with the public. For example, in the case of a passenger's forcible removal from a flight in April 2017, the defensive tone of the firm's tweets only poured fuel on the fire and created additional backlash (Ross 2017).

The few examples briefly discussed above highlight the importance of firms' social media communication and the significance of its consequences for firms. Despite this fact, past studies have given relatively greater attention to consumers' communication on social media (e.g., Tirunillai and Tellis 2012; You, Vadakkepatt, and Joshi 2015), and little attention has been paid to firms' social media communication, and more specifically, to the implications of different social media strategies employed by firms. In fact, in recent years there have been calls for research on this topic, suggesting that identifying factors that impact the effectiveness of firms' social media communication is of the utmost importance (e.g., Aral, Dellarocas, and Godes 2013; Kumar et al. 2016).

In its two essays, the current dissertation tries to respond to these calls, by exploring the phenomenon of firms' communication on social media and shedding light on how it can impact firm performance. It explores this phenomenon in two theoretically and practically important contexts: established firm and nascent firms. Established firms have a strong presence on social media. For example, approximately 83% of Fortune 500 companies have active Twitter accounts (Adweek 2014). Moreover, the social media presence of large firms is managed by an average of thirteen employees (Miller and Tucker 2013). Similarly, social media is an important communication means for entrepreneurial firms (e.g. new ventures). This is because these young firms are constrained by a lack of structural and financial resources (e.g. Bresciani and Eppler 2010), and thus have limited access to the traditional means of communication (e.g. advertising campaigns). The two essays are introduced below.

The first essay (Chapter 2) explores how different modes of social media communication can impact firm performance independently and jointly. Specifically, business reports and academic research works have generally encouraged practitioners to actively leverage the unique opportunity offered by social media to simultaneously broadcast to the mass audience (impersonal communication) and interact with individuals (personalized communication). However, little empirical evidence supporting this recommendation exists.

This essay tries to explore this topic by understanding how these communication modes impact firm performance independently and jointly. Impersonal communication is controlled by the firm, targets mass audience, and is mainly used for brand building purposes through promoting a consistent and positive image (e.g. Hewett et al. 2016; Colicev et al. 2018). By contrast, personalized communication has a reactive and thus less controlled nature, is topic-specific and is mainly used for addressing questions and complaints (Huang, Baptista, and Newell 2015). Given the mentioned, as well as other differences between these two modes of communication, it is both theoretically and practically important to explore the direct impact that each has on firm performance, as well as the indirect effect that each exerts (by moderating the impact of the other communication mode).

Exploring this topic is important in that most extant studies on firms' social media communication have either examined the aggregate-level impact of social media communication (e.g., the impact of the cumulative number of a firm's tweets, retweets, and replies), or have been limited to impersonal communication (e.g., Colicev et al. 2018; Miller and Tucker 2013; Kumar et al. 2016). This leaves the impact of personalized communication, as well as the interactive impact of impersonal and personalized communication relatively unexplored. This study utilizes a multi-source dataset to empirically address the above question.

The second essay (chapter 3) highlights the importance of managing the lingual aspects of social media communication for B2B new ventures. Social media, given their ubiquity, reach, and low costs, present an opportunity for these young firms to communicate with potential investors and future stakeholders. Importantly, new ventures can utilize social media to signal their marketing capabilities to potential investors. Since marketing is critical to a new venture's success, and inefficient marketing is a major reason for a new venture's failure (Politis 2005), investors pay special attention to the new venture's marketing-related potentials, and as such signaling these potentials may significantly impact ventures' success in raising capital funds. This means that managing social media communication is of paramount importance for new ventures. This, for B2B new ventures whose organizational field is complex and consisted of customer and competitor firms which often belong to distinct industries with differing norms, means deciding which organizational norms of lingual usage in social media should be followed and which norms should a venture get distance from. This essay builds on the literatures of marketing capabilities (e.g. Josephson et al. 2016), strategic similarity and dissimilarity (e.g. Deephouse 1999), and comparative linguistics (e.g. Johnson et al. 2015) to address this question. More specifically, this essay demonstrates how lingual similarity of a B2B new venture's social media communications to those of its competitors and customers, can signal important information about the venture's marketing capabilities, thus impacting its success in fundraising.

CHAPTER 2

Essay 1: How Do Different Modes of Social Media Communication Can Impact Firm Performance

Abstract

The emergence of social media has changed how firms communicate with their audiences. Business reports and academic research have generally encouraged practitioners to actively leverage the unique opportunity offered by social media to simultaneously broadcast to the mass audience (impersonal communication) and interact with individuals (personalized communication). However, little empirical evidence supporting this recommendation exists. The current research builds on the literatures of firms' social media communication, and integrated marketing communication to explore this topic. Using a dataset, which includes the tweets, as well as financial data of S&P 500 firms present on Twitter, we find that both impersonal and personalized communication have a positive direct effect on firm performance. However, this study paints a more intricate picture by showing that each of these two modes of communication diminishes the impact of the other. We argue that this suppressive effect is due to the differential nature of them, and the different objectives served by each. Importantly, the findings remain qualitatively robust after accounting for endogeneity by using internal and external instruments.

Keywords: Social media, Impersonal communication, Personalized communication, Financial performance.

2.1. Introduction

The tremendous growth of social media has dramatically changed consumers' and firms' communication. Consumers are increasingly relying on social media platforms such as Twitter for communicating and obtaining various types of information (Barthel et al. 2015). Similarly, firms are increasingly investing in marketing channels like Facebook and Twitter. In fact, social media is consuming an increasingly larger portion of firms' marketing budgets. The social media marketing's share of the firms' total marketing budget is projected to increase from 10.5% in 2017 to about 18.5% in 2022 (CMO Survey 2017).

Past studies have given relatively greater attention to consumers' communication on social media (e.g., Tirunillai and Tellis 2012; You, Vadakkepatt, and Joshi 2015). More recent research has started to examine firms' social media communication,[1] revealing its positive impact on consumer mindset metrics, such as brand awareness and satisfaction (e.g., Risius and Beck 2015; Miller and Tucker 2013), as well as on consumer profitability (Kumar et al. 2016).

To some extent, the benefits of social media are due to their dual capacity: they provide firms with the unique opportunity to establish *impersonal* as well as *personalized* communication, disseminating useful information to various stakeholders and addressing their questions and concerns. Personalized (impersonal) communication refers to any social media communication that is (not) directed toward a specific user, i.e. a specific Twitter handle[2]. For example, on Twitter, when a firm posts contents (i.e. tweet), and when it retweets[3] other users' tweets, it is engaging in impersonal communication, as these communications don't address a

[1] In this study, "communication", and "social media communication" are used interchangeably.
[2] Goh et al. (2013) use *directed* and un*directed* communication, respectively, to refer to these modes of communication. However, we believe that above terminology is more consistent with our theory.
[3] Although firms don't have control over the content of the tweets that they retweet, as will be discussed later, they have control over which tweets to retweet.

specific user. By contrast, when it responds to a specific user's tweet (e.g. an airline resolving passenger issues on Twitter in real-time), it is engaging in personalized communication (e.g. Hewett et al. 2016).

Utilizing these two communication modes enables a firm to reduce consumers' information asymmetry and handle customers' questions and complaints at the same time, which could potentially improve such consumer-mindset metrics as customer satisfaction, which have been shown to positively impact the market value of the firm (e.g. Dotzel, Shankar, and Berry 2013).

Although social media give firms unprecedented flexibility in their communications, which can potentially lead to better financial performance, they present managers with a challenging task: understanding how the two modes of communication (i.e., impersonal and personalized communication) should be employed in order to maximize the overall return. To achieve this objective, a first step would be to understand how these communication modes impact firm performance independently and jointly. This is an important question from both theoretical and practical perspectives.

Theoretically, there have been calls for research on firms' social media communication in recent years, suggesting that identifying factors that impact the effectiveness of these communications is of the utmost importance (e.g., Aral, Dellarocas, and Godes 2013; Kumar et al. 2016). However, most extant studies on this topic have either examined the aggregate-level impact of social media communication (e.g., the impact of the cumulative number of a firm's tweets, retweets, and replies), or have been limited to impersonal communication (e.g., Colicev et al. 2018; Miller and Tucker 2013; Kumar et al. 2016). This leaves the impact of personalized communication, as well as the interactive impact of impersonal and personalized communication relatively unexplored.

From a practical perspective, according to CMO Survey (2016), four out of five marketers are unable to quantify the impact of social media on their business performance. Given the scarcity of empirical insight about the impact of communication modes on firms' performance, firms are still experimenting with their use of social media (Gong et al. 2017). For instance, some firms view Twitter as a broadcasting medium, and mainly use it for impersonal communication, while others see it as a vehicle for personalized communication with their target audiences (Hewett et al. 2016). Overall, there is significant heterogeneity in firms' social media communication practices even within the same venue (e.g. Twitter) and among firms from the same industry. This could potentially lead to differences in the effectiveness of these practices. Indeed, recent empirical findings provide evidence that the effectiveness of social media communication significantly varies across firms (e.g., Swayne 2015; Hewett et al. 2016).

The current research aims to address this gap by providing an integrative perspective that considers the impact of communication modes both independently and interactively. In so doing, it distinguishes between two broad communication modes on social media, namely, impersonal communication and personalized communication, consistent with past research (e.g., Risius and Beck 2015; Etter 2014; Goh, Heng, and Lin 2013). Impersonal communication is controlled by the firm, targets mass audience, and is mainly used for brand building purposes, through promoting a consistent and positive image (e.g. Hewett et al. 2016; Colicev et al. 2018). By contrast, personalized communication has a reactive and thus less controlled nature, is topic-specific and is mainly used for addressing questions and complaints, and as such, can conflict with the positive brand image the firm tries to promote (Huang, Baptista, and Newell 2015).

Given the mentioned, as well as other differences between these two modes of communication, it is both theoretically and practically important to explore the direct impact that each has on firm performance, as well as the indirect effect that each exerts (by moderating the impact of the other communication mode). In order to test these ideas, we compile a cross-industry dataset based on all of the firms with an active Twitter account, which are listed on the S&P 500 stock market index, and explored the direct and indirect impacts of impersonal and personalized communication on firm performance (Tobin's Q). Tobin's Q is a good proxy for firm performance and is the most widely used approach for capturing changes in the value of a firm's intangible assets (Dotzel et al. 2013).

Our dataset includes the tweets of 375 S&P 500 firms as well as their advertising expenditures and financial/accounting data (collected from such sources as Twitter, Kantar Media's Ad$spender, and COMPUSTAT) during the period of 2014-2015. Controlling for observed and unobserved heterogeneity in firm performance, we demonstrate that both impersonal and personalized communication are positively associated with firm performance (Tobin's Q). More importantly, we show that each of these communication modes suppresses the positive impact that the other has on firm performance. Building on the literature of integrated marketing communication, we argue that this suppressive effect is due to the differential nature of different modes of communication and the entirely different objectives each serves. The findings remain qualitatively robust after accounting for possible endogeneity by using internal and external instruments (see Germann, Ebbes, and Grewal 2015).

Our follow-up investigation breaks down impersonal communication into tweeting and retweeting and shows that tweeting and replying (i.e. personalized communication) are positively associated with firm performance. By contrast, retweeting has no significant impact on firm performance. Moreover, retweeting does not have a significant interaction with tweeting, but it weakens the impact of replying on firm performance. Finally, tweeting and replying weaken the positive impact of each other on firm performance

The current research contributes to the social media marketing theory and practice by painting a more intricate picture of the performance implications of firm communication on social media. By demonstrating the positive impact of different modes of social media communication on firm performance, it adds to past work in providing justification, from a shareholder wealth perspective, for the upward trend of investment in social media by firms. Unlike previous research which has explored the aggregate impact of firms' social media communication (Colicev et al. 2018), the current work explores the impact of each communication mode on firm performance, thus offering a more detailed account of the impact of social media communication.

Notably, the suppressive effect revealed in this study implies that the effects of communication modes are more intricate than a sole focus on the main effects would suggest. This finding is important in that, business reports (e.g., LoyaltyOne 2012) as well as academic research (e.g., Kumar et al. 2016; Goh et al. 2013) have generally encouraged practitioners to actively leverage the opportunity, brought about by social media, to simultaneously *broadcast to the mass audience* and *be connected to individuals*. Although the current work provides support for the positive impact of different communication modes, it reveals that neglecting the interactive relationship between them can lead to misleading conclusions. Thus, the current work highlights that executives need to have an integrated perspective when formulating their social media strategy and consider different modes of communication as parts of a unified system in order to maximize their total impact. Although past research has suggested that different modes of communication on social media may be unable to support each other (Huang et al. 2015), this study is the first to explore this possibility empirically.

The remainder of the paper is organized as follows: We first review past research on firms' social media communication and formulate our hypotheses based upon past research on multi-channel communication and integrated marketing communication. Then, we describe the empirical strategy and present the results. The paper concludes with a discussion of theoretical and managerial implications, as well as avenues for future research.

2.2. Theoretical Background

2.2.1. Social Media

The profound impact of social media on the business environment has sparked an interest in research on this topic. Past research has given relatively greater attention to consumer-generated content. Research in this area has shown that consumers' communication can impact a wide variety of outcomes, such as sales (e.g., You et al. 2015; Chevalier and Mayzlin 2006), bank deposits (Hewett et al. 2016), and website growth (Trusov, Bucklin, and Pauwels 2009). However, given the potential of social media for firm marketing communication and the increasing portion of firms' marketing budget allocated to social media, researchers have started to explore the impacts that firm communication through social media can have on business outcomes. This stream of research has revealed the positive impact of firms' social media communication on consumer mindset metrics (e.g., public awareness and perceptions of the firm; Risius and Beck 2015; Miller and Tucker 2013), as well as on purchase and profitability (Danaher and Dagger 2013; Kumar et al. 2016).

What is missing in this literature, though, is a direct examination of the impact of different communication modes, which could potentially help us understand why some firms are more successful in their social media communication than others (e.g., Swayne 2015; Hewett et al. 2016). In general, a firm's communication on social media can be categorized into impersonal or personalized communication (Goh et al. 2013). On Twitter, impersonal communication is accomplished through tweeting and retweeting. Through tweeting, firms communicate their original content to their audience, while by retweeting, firms repost the content generated by other entities on social media. by which firms address their entire audience. Regardless of the origin of the content, though, by impersonal communication, firms communicate to the entire audience base without targeting a specific recipient. Through personalized communication, by contrast, firms can interact with others on a one-on-one basis. Although in some cases, firms initiate this type of communication by proactively addressing a specific recipient, what is more common is that firms pinpoint others' tweets (those that have a bearing on the firm) and reply to them. Indeed, past research shows that firms vary significantly with regard to how they combine these modes of communication (e.g., Hewett et al. 2016).

As these communication modes serve different purposes and differ in many aspects, it is necessary to explore their independent, as well as interactive effects on firm performance. Past research in this area has mainly explored either the aggregate-level impact of social media communication (e.g., the impact of the cumulative number of a firm's tweets, retweets, and replies) or the impact of impersonal communication (e.g., Colicev et al. 2018; Miller and Tucker 2013; Kumar et al. 2016), leaving firms' personalized communication relatively unexplored. For instance, Colicev et al. (2018) show that the cumulative number of a firm's Facebook posts, tweets, retweets, and replies has a positive and marginally significant impact on abnormal returns. Moreover, past research has ignored the interplay of these modes of communication (i.e. their possible interaction).

One notable exception is recent research by Hewett et al. (2016), which discusses this issue briefly, though not as the main topic of the research. As part of their research, the authors examine how the quantity of firm communications on Twitter can impact consumer deposits in four large U.S. banks. They find notable differences in the effectiveness of Twitter communication across banks. For example, they find that the quantity of tweets by Bank of America positively impacts customer deposits, but this is not the case for other banks. They suggest that this might be due to differences in how different banks use social media. Specifically, they observe that Bank of America uses Twitter mainly for customer service and personalized communication, while other banks mainly use Twitter as a means for impersonal communication (i.e., broadcasting and promotional activities). However, they do not empirically test this possibility.

The current work hopes to contribute to this stream of research by exploring the independent as well as interactive impacts that different modes of communication can have on firm performance (Figure 1 presents our proposed conceptual framework). This research is in line with a view of social media communication as a multifaceted construct (Kumar et al. 2016) and responds to various calls for research on firms' social media communication (e.g., Aral et al. 2013). In the next subsections, we briefly discuss different modes of communication on social media (with a focus on Twitter, as the context of the present study) and their possible impact on firm value.

2.2.2. Direct Effects of Social Media Communication Modes on Firm Performance

In the current work, we argue that both impersonal and personalized communication will positively affect firm performance. This prediction is broadly consistent with past research, which has shown that firm communication (e.g. advertising) is generally associated with positive outcomes such as brand equity (Keller and Lehmann 2006), customer loyalty, and repurchase intentions, and thus impacts firm profitability (Joshi and Hanssens 2008, Luo and Donthu 2006).

Impersonal communication. Impersonal communication is a means for quickly broadcasting a firm's message (Lee, Hutton, and Shu 2015). It is a form of one-way communication that addresses the whole audience base and does not target a single recipient (Goh et al. 2013). As mentioned before, most of the past research on firms' social media communication has focused on impersonal communication. Although this stream of research has provided support for the positive consequences of impersonal communication, it has mostly focused on consumer-level metrics. For example, Goh et al. (2013), in their study of the Facebook page of an Asian retailer, showed that impersonal communication is positively associated with purchase expenditures. Similarly, research shows that impersonal communication improves brand awareness (Risius and Beck 2015), as well as customer spending, cross-buying behavior, and profitability (Kumar et al. 2016). Despite the fact that these studies have shed light on important benefits of impersonal communication, measures used in these studies do not reflect shareholder wealth (Luo, Zhang, and Duan 2013).

In the current work, we argue that impersonal communication can positively impact financial performance for several reasons. First, it is a form of communication that is fully controlled by the firm and is mainly used to build a positive brand image[4]. As such, it is expected to positively impact brand equity (Schivinski and Dabrowski 2016). Indeed, research shows, firms' communication repetition increases credibility as it enhances familiarity to brand

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[4] Although firms do use impersonal communication to make announcements in the wake of negative events, these uses are exceptions, not the rule, as impersonal communication mainly uses promotional language to build a positive brand image (e.g. Hewett et al. 2016).

attributes (Arkes et al. 1991). In this sense, the role of impersonal social media communication is similar to that of advertising (e.g., Kumar et al. 2016) in communicating firm-related information (e.g., offerings, prices, promotions, etc.), building brand awareness, and in general, reinforcing the firm's value propositions (e.g., Risius and Beck 2015; Mandviwalla and Watson 2014). As such, it is likely to increase firm performance, much like advertising does (e.g., Dekimpe and Hanssens 2007).

Second, since a firm's impersonal communication reduces the information asymmetry problem for customers by providing relevant information (e.g., Goh 2013), it can also increase customer satisfaction, which, has been shown to positively impact firm performance (e.g. Dotzel et al. 2013). Moreover, a firm's impersonal communication on social media can provide information about the firm's marketing strategy. The stock market is likely to respond to the information transmitted through firms' impersonal communication very quickly, given that this type of content is highly contagious and visible (Luo et al. 2013). Based on this discussion, we hypothesize:

> H_1: Firms' impersonal communication on social media is positively associated with financial performance.

Personalized communication. Personalized communication refers to any social media communication that is directed to a specific individual (i.e. a specific Twitter account). This communication mode has a reactive and less controlled nature, is topic-specific and is mainly used for addressing questions and complaints. Although, in the marketing literature, evidence about personalized communication is less common than impersonal communication, past research has revealed the positive consequences of firms' personalized communication on social media at the individual level, including its positive impact on consumers' purchase expenditures (Goh et al. 2013) and brand awareness (Risius and Beck 2015).

Extant literature on this mode of communication, however, has been either limited to one firm (e.g., Goh et al. 2013) or has not provided direct, empirical evidence of the impact of personalized communication (e.g., Hewett et al. 2016). In addition, past work has not explored the possible impact of personalized communication on shareholder wealth. Exploring this possibility is both theoretically and practically important because there is evidence showing that firms may be underutilizing personalized communication (e.g., Burton and Soboleva, 2011).

In our current work, we argue that a firm's personalized communication on social media can positively impact its performance. This is broadly because personalized communication can improve a firm's prospect of success and profitability by improving and signaling its social capital, as well as by increasing its insight about the market. In general, one-to-one communication can create social capital (Mandviwalla and Watson 2014). As Hallahan (2001) argues, interactivity is a key in creating and maintaining social assets. Personalized communication can exert its impact on a firm's social capital in several ways. Past research has highlighted the importance of addressing consumer questions and complaints (e.g., resulting from service failure; Modi, Wiles, and Mishra 2015). Responding to customers' comments and addressing their complaints demonstrate the firm's customer orientation and its appreciation for customers (Risius and Beck 2015). In addition, it may increase satisfaction and trust from the complainant, as well as other observers (e.g., followers; Gu and Ye 2014), giving the firm an even higher level of credibility (Breitsohl, Khammash, and Griffiths 2010). Indeed, customer satisfaction has been shown to improve firm value (e.g., Luo, Homburg, and Wieseke 2010).

Finally, personalized communication is, in general, topic-specific, rich in useful content and emotionally close, and as such, it can strengthen relationships (Oswald, Clark, and Kelly 2004).

Aside from its impact through improved customer satisfaction, from an investors' perspective, personalized communication provides stakeholders (e.g., investors) with information about a firm's interactions with its existing and potential customers (Luo et al. 2013). It therefore signals the firm's relational bonds with customers as a valuable asset, which can improve expectations about the firm's long-term profitability. This is because investors have limited attention (e.g., Hirshleifer and Teoh 2009) and they do observe social media[5] (Chen et al. 2014). Such visible signals can, thus, have a significant impact on their expectations (Luo et al. 2013).

In addition to its impact on social capital, personalized communication can entail informational benefits. It evokes norms of reciprocity (Burke, Kraut, and Marlow 2011), encouraging individuals to interact with the firm. These interactions may provide firms with a valuable source of market information. According to the market orientation literature, firms can leverage such information to make better marketing mix decisions (e.g., Hewett et al. 2016), which can lead to improved expectations of firm performance.

> H_2: Firms' personalized communication on social media is positively associated with financial performance.

2.2.3. Interactive Effect of Communication Modes on Firm Performance

Although it is important to understand how different modes of communication directly impact performance, such an investigation does not capture the totality of the impact of these firm initiatives. This is because each mode of communication can have an indirect impact on

[5] Brunswick group's study on investors indicates that approximately 43% of them consider communications on social media as an important factor impacting their investment decisions (Tirunillai and Tellis 2012).

firm performance by moderating the impact of the other mode. Indeed, a large body of research has demonstrated that marketing communication operates as a system comprised of different channels and message types, and each element of this universe can moderate the impact of other elements (e.g., Sridhar and Sriram 2015; Naik and Raman 2003).

Interactive relationships can exist on social media, since social media communication has an extremely dynamic nature. Impersonal and personalized communication differ in their nature (e.g., addressing mass audiences vs. individuals) and can serve different objectives (reinforcing value propositions vs. building customer relationships). Given their differences, a complex interplay could exist, whereby each communication mode might moderate the impact of the other on firm performance. In other words, the marginal impact of each communication mode can be moderated by the other mode.

In the current work, we argue that social media communication modes can suppress the impact of each other. Past research has reported instances of negative interactions, suggesting that firms should consider the possibility of suppressive effects when making marketing decisions (e.g., Sridhar and Sriram 2015). This means that, all else held equal, one marketing action could diminish the marginal effect of another. For example, Gopal, Li, and Sankaranarayanan's (2011) study on two channels of keyword-based ads (search channels and content channels) demonstrates that each channel can reduce the effectiveness (i.e., click-through rate) of the other channel. Sridhar and Sriram (2015) empirically show that online advertising is responsible for as much as 17% of the loss in print advertising. Other research documents suppressive effects between advertising and promotions (Naik, Raman, and Winer 2005).

Most of past work on suppressive effects in the context of marketing communication has focused on multi-channel communication, and this literature provides us with little information about the possibility of within-channel suppression. Although past research has suggested that different modes of communication on social media may be unable to support each other (Huang et al. 2015), extant literature has not explored this possibility empirically. In the current work, we argue that, because of their significant differences, the two modes of social media communication may negatively interact in affecting firm performance. We hold that the differential natures of the two modes of communication, as well as the different objectives they serve, might make thematic integration difficult, thus leading to a suppressive effect. Research on integrated marketing communication points to the importance of adopting an overarching communication theme across all communication efforts (e.g., Sheehan and Doherty 2001), and argues that the failure to develop a cohesive message can lead to suppressive effects among communication efforts. Importantly, such a failure can stem from jointly using communication techniques that differ in nature. For example, Naik et al. (2005) argue that while the main purpose of advertising is boosting brand image, promotion erodes brand equity as it draws attention to price. Based on this idea, they demonstrate that each of these two activities can attenuate the effectiveness of the other.

With regard to social media communication, different modes of communication differ in their nature and, consequently, may negatively impact the effectiveness of each other. To explain, impersonal communication is a one-way communication, and as such, does not target a particular individual (Goh et al. 2013). Moreover, given its broadcasting nature, firms' impersonal communication employs a broad and abstract language and is low in specificity. By contrast, as its name implies, a firm's personalized communication on social media has a conversational, one-on-one nature. Also, unlike impersonal communications, personalized communication is generally concrete and topic-specific (Oswald et al. 2004). This type of communication tends to be rich in content that is useful and relevant to the person it addresses, but, since it mainly deals with the questions and complaints of a specific individual, it tends to be low in relevance to a broad audience. Importantly, this can diminish the overall perceived usefulness of a firm's social media communication. Given that individuals, in the online environment, are much less tolerant of irrelevant messages (Bacile et al. 2014), they may unfollow the firm's Twitter handle, and this can decrease the reach of the firm's impersonal communication.

Importantly, Burton and Soboleva (2011) have provided initial support for this idea. In their study of social media communication of six American and Australian firms, they find a negative correlation between the percentage of personalized communications and the number of account followers (which means a decrease in the reach of impersonal communication). They argue that personalized communications of a firm on its Twitter account might make the content irrelevant and uninteresting to the broad audience. The authors, however, do not test the possible negative impact that personalized communications can have on the effectiveness of impersonal communications.

In addition, when a firm tweets (which is a form of impersonal communication), it is voluntarily disclosing information. It is known that firms' voluntary information disclosure, in general, suffers from selection bias. In other words, voluntary disclosure mainly includes positive information about the firm, with the messages sometimes being unrealistically positive (e.g., Kim and Lyon 2015). This is consistent with the social media literature which suggests that the role of impersonal communication is building brand awareness and reinforcing the firm's value propositions (e.g., Risius and Beck 2015; Mandviwalla and Watson 2014). Consequently, this mode of communication is typically consistent and coherent over time (Gensler et al. 2013) and often has a promotional tone irrespective of the real quality of the brand and its products (e.g., Colicev et al. 2018; Hewett et al. 2016). By contrast, personalized communication on social media focuses on building and maintaining relationships, most substantially by responding to customers' questions and complains (e.g., Risius and Beck 2015; Hewett et al. 2016). Consequently, personalized communication is less likely to employ a promotional tone (Hewett et al. 2016; Goh et al. 2013). When it deals with complaint handling, personalized communication also involves accepting a misfit between the image that the company tries to convey and its actual behavior, thus potentially conflicting with the image promoted through impersonal communication. Finally, personalized communication can inadvertently publicize consumers' negative brand experiences to a much larger audience (followers and even non-followers) as consumers' complaints will be displayed on both the firm's Twitter account (viewable by everyone), as well as the followers' timeline. Although a firm's responses to the complaints could mitigate the adverse impact of the complains, and even, as we hypothesize, might even benefit the firm by increasing customer satisfaction and firm's credibility (see H_2), it still can damage the positive image the firm tries to build through its impersonal communication.

In sum, differences between the two modes of social media communication can make thematic coordination difficult, leading to inconsistent messages, which can result in each type of communication suppressing the effect of the other. Based on these arguments, we hypothesize:

> H_3: There is a negative interactive effect between personalized and impersonal communications.

2.3. Method

2.3.1. Sample and Data

In order to test the hypotheses, we compiled a unique dataset, which includes social media communication, as well as financial and accounting data from a sample of S&P 500 firms. Twitter activity is a useful proxy for social media communication, and using Twitter data in academic research allows for easy replication (Twitter data is publicly available, and can be purchased as well; Hewett et al. 2016). Moreover, established firms have a strong presence on Twitter. For example, approximately 83% of Fortune 500 companies have active Twitter accounts (Adweek 2014). Moreover, the social media presence of large firms is managed by an average of thirteen employees (Miller and Tucker 2013).

We first started with all of the firms listed on the S&P 500 stock market index in 2014. We then surveyed the website of each firm to identify its official Twitter account (if any)[6]. This ensured that the identified Twitter account belongs to and is managed by the firm. This resulted in identifying a total of 375 firms with a Twitter account at the time of data collection. We then designed and developed a python engine for web scraping to collect information from Twitter. We crawled the Twitter page of each firm to collect tweets made by it. Using this method, we downloaded all of the tweets posted on each firm's Twitter handle during 2014 and 2015.

Following past research on Twitter (e.g., Hewett et al. 2016; Boyd, Golder, and Lotan 2010), we labeled all of the tweets containing a username at the beginning (i.e., addressing an individual user[7]) as personalized, and labeled the remaining tweets as impersonal[8]. When posting a long message on Twitter, firms use one of the two following practices to overcome the character limitation. Sometimes, firms split the message into several successively numbered tweets. Alternatively, they sometimes post the first part of the message as a tweet and include the rest of the message as multiple replies to the first tweet. In both cases, we labeled all of the

[6] Four firms in our sample owned more than one Twitter account. Excluding these firms didn't affect the results.

[7] "Individual user" means a Twitter handle. It can belong to an individual, and organization, or any other entity.

[8] Please see the "further analysis" section for an additional analysis based on a more fine-grained categorization of tweets.

tweets that belong to one message as one impersonal tweet. Another common practice on Twitter is that a firm posts a tweet, to which a user reacts, and the firm, then, replies to that individual. In such cases, we labeled the firm's original tweet as impersonal tweet, and the replies that the firm makes to that user as impersonalized tweet.

We complemented the social media data with firm financial data from the *COMPUSTAT* quarterly database. Finally, in light of the documented impact of advertising expenditures on firm performance (Joshi and Hanssens 2010) and given the fact that *COMPUSTAT* does not provide quarterly advertising expenditures data, we concatenated our data with quarterly advertising expenditures data from Kantar Media's Ad$spender. Our final sample included 2948 observations over an 8-quarter period.

2.3.2. Measures

Firm performance is measured using quarterly Tobin's q. Tobin's q is a forward-looking market value measure that captures both the short-term performance, as well as the long-term prospects of a firm (Germann et al. 2015). Importantly, Tobin's q is the most widely used approach for capturing changes in the value of a firm's intangible assets (Dotzel et al. 2013), such as the brand equity that can be driven by a firm's social media communications. Using Tobin's q is appropriate for a sample like ours, which includes firms from different industries (Montgomery and Wernerfelt 1988). Consistent with past research (e.g., Dotzel et al. 2013; Lee and Grewal 2004), we calculated Tobin's q as (market value of common stock shares + book value of preferred stock + book value of long-term debt + book value of inventories + book value of current liabilities – book value of current assets)/(book value of total assets).

The independent variables are the number of impersonal and personalized tweets made by each firm, aggregated into quarterly counts. Past marketing research (e.g., Colicev et al. 2018;

Hewett et al. 2016; Kumar et al. 2016) as well as information systems research (e.g., Miller and Tucker 2013) have used the frequency of posting to study the impact of social media communication. Moreover, measuring variables in quarterly intervals rather than in annual intervals is appropriate not only because the period we study is short (two years), but also because firms' social media communication can vary significantly from quarter to quarter. Past research has recommended measuring variables in quarterly intervals in contexts characterized by rapid changes in firms' behavior (e.g., Rindova, Ferrier, and Wiltbank 2010). In line with this idea, variables measured quarterly have been used in recent social media research (e.g., Hitt, Jin, and Wu 2016).

2.3.3. Controls

To obtain robust estimates of the effects of the focal variables, we followed extant research (e.g., Feng, Morgan, and Rego 2015; Tirunillai and Tellis 2012; Josephson, Johnson, and Mariadoss 2016; Dotzel et al. 2013), and control for a comprehensive set of potentially confounding factors. First, we used the Ad$spender dataset of Kantar Media to determine firm-level advertising spending. Ad$pender includes a firm's advertising expenses in 18 media vehicles (e.g., TV, radio, internet). We summed each firm's expenses across these vehicles, and calculate *Advertising intensity* as advertising expenses scaled by sales (e.g., Qian 2002). We obtained data on other control variables from the COMPUSTAT quarterly database. Specifically, we operationalized *R&D intensity* as total R&D expenditures scaled by sales. We controlled for c*ompetitive intensity* using the reciprocal of the Hirschmann–Herfindahl index (i.e., the sum of the squared market shares for all firms in each 4-digit SIC code; Feng et al. 2015).

Return on assets was measured as income before extraordinary items scaled by total assets. *Leverage* and *Organizational slack* were operationalized as long-term debt scaled by total assets

(Dotzel et al. 2013), and net cash flow from operating activities scaled by total assets, respectively. *Industry size* was measured by totaling the sales of all firms in the same industry. *Cost of goods sold*, as well as *quarter dummies*, were also included in the model. Finally, we included the *average length of a firm's tweets*. The Appendix includes a table summarizing the main measures, as well as their alternatives.

2.3.4. Specification

To test the direct effect hypotheses, the following equation was estimated:

(1) $$TOBINQ_{it} = \alpha_0 + \alpha_1 Impersonal_{it} + \alpha_2 Personalized_{it} + \alpha_3 X_{it} + \epsilon_{it}$$

To evaluate the interactive effect, the following equation was estimated:

(2) $$TOBINQ_{it} = \alpha_0 + \alpha_1 Impersonal_{it} + \alpha_2 Personalized_{it} + \alpha_3 ImpersonalPersonalized_{it} + \alpha_4 X_{it} + \epsilon_{it}$$

In these equations, subscript *i* represents the firm and subscript *t* represents the quarter. TOBINQ is Tobin's q. α_1 and α_2 represent the main effects of impersonal and personalized communication. α_3 represents the interaction between impersonal and personalized communication. α_4 captures the effects of a vector of control variables which includes industry-level controls (competitive intensity, and industry size), firm-level controls (advertising intensity, R&D intensity, leverage, organizational slack, cost of goods sold, and return on assets), communication-level control (average length of tweets), as well as quarter dummies. Finally, ϵ is an error term.

Before estimating the models, all variables were standardized to help aid in interpretation and to reduce possible multicollinearity (e.g., Josephson et al. 2016). Given the panel structure of the data, a Hausman test was run in order to select the appropriate random-effects or fixed-effects model. The results of this test failed to reject the null hypothesis that the firm-level effects are adequately modeled by a random-effects model ($p > 0.10$). Searching for a proper random-effects estimation, we conducted Breusch–Pagan and Wooldridge tests to better understand the structure of the data. The results of the Breusch–Pagan test indicated the presence of heteroskedasticity (χ^2 (15) = 567.77, $p < 0.001$). Moreover, the F-statistic for the Wooldridge test for autocorrelation was 33.06 (p < .01). This confirmed the presence of first-order autocorrelation. Accordingly, a feasible Generalized Least Square (GLS) regression with corrections for panel-specific autocorrelation and panel-specific heteroskedasticity was used to estimate the coefficients of the proposed models.

2.4. Results

Table 1 reports descriptive statistics of the data. We note that all the VIF scores are within the acceptable range (ranging from 1.02 to 2.77), and thus the threat of multicollinearity is low (Hair et al. 2010). Within the time frame of the study, firms in our sample posted on an average 162 impersonal tweets per quarter and 60 personalized tweets, with each tweet including on average about 13 words. Average Tobin's Q (total market value divided by the total asset value) in the sample was 2.17, which implies that stock of our sample firms was more expensive on average than the replacement cost of their assets.

The main results are presented in Table 2. In model 1 only control variables are included as covariates. Model 2 presents the direct-effects model. As expected, return on assets, organizational slack, and advertising expenditures are positively associated with firm performance. However, R&D expenditure, and financial leverage are not significantly associated with performance. Moreover, there is a negative association between firm performance and the cost of goods sold, industrial size, and industry competitiveness. The results also indicate a negative effect of tweet length. This is consistent with industry (Salesforce 2012), as well as academic (Comarela et al.

2012) studies, which have reported that shorter tweets are more effective (e.g., more likely to be retweeted) than longer ones.

Consistent with H_1, the results of Model 2 show that there is a positive association between impersonal communication and firm performance after accounting for firm-level, industry-level, and tweet-level factors. A similar association is found between personalized communication and firm performance. Model 3, however, provides a more intricate picture by highlighting a tension between these two types of communication. Consistent with H_3 this model shows that although the two modes of communication have a positive association with firm performance, each weakens the positive impact of the other, as indicated by the negative coefficient on the interaction term. Moreover, employing Wald test, it was found that model 2 provides a significantly better goodness-of-fit compared with model 1 ($p<0.001$), and that model 3 provides a significantly better goodness-of-fit compared with model 2 ($p<0.001$). To the best of our knowledge, this analysis provides the first evidence of the suppressive effect between impersonal and personalized social media communication. We next perform additional analyses to ensure the robustness of our results.

2.5. Endogeneity Correction

A firm's behavior on social media may be influenced by unobserved factors, raising concerns of endogeneity. Although we have controlled for important variables that can impact firm performance, other variables may simultaneously influence a firm's behavior on social media, as well as the firm's performance, rendering our independent variables endogenous. To empirically address the endogeneity concerns, we reestimated our model by separately utilizing internal and external instrumental variables. First, we re-estimated our model using a control function approach (Petrin and Train 2010). Second, we utilized the Arellano-Bover/Blundell-Bond system of generalized method of moments (GMM) estimator (e.g., Arellano and Bond 1991). These two approaches have been widely applied in past marketing research to address endogeneity concern (e.g., Eilert et al. 2017; Rego, Morgan, and Fornell 2013; Germann et al. 2015). Evidence of the robustness of our results to these two additional tests will increase the confidence in our findings.

First, we utilized a control function approach to account for the possible endogeneity of the two modes of communication. This approach is based on including a term (i.e., a control variable) for unobserved variables in the regression model to decrease the correlation between the possibly endogenous variables and the error term (e.g., Eilert et al. 2017). This approach involves two steps. The first step involves a separate estimation for each potentially endogenous variable (i.e., each communication mode). In our case, this means defining two estimations for impersonal and personalized communication, respectively. More specifically, in each of the two estimations, one endogenous variable is regressed on the control variables of eq. (2), as well as a variable that satisfies the exclusion restriction criterion (i.e., it correlates with the communication mode, but not directly with the error). In the second step, the predicted residuals from these two estimations are included in the main regression model. As a result, the concern of endogeneity will be mitigated, and unbiased coefficients will be generated (Eilert et al. 2017).

In the search for variables that satisfy the exclusion restriction, we followed past research, which has utilized industry-based excluded variables (e.g., Saboo et al. 2017; Germann et al. 2015). Specifically, for impersonal (personalized) communication, we selected the average impersonal (personalized) social media communication by peer firms as the instrumental variables. Peer firms are firms in the same two-digit SIC code as the focal firm (e.g., Germann et al. 2015). For firm *i* in industry *j* (which includes N firms), we calculated the average impersonal (personalized) social media communication by peer firms as the sum of impersonal (personalized) social media communication by firms in industry *j* other than firm *i* divided by N_j-1.

We believe the industry's average social media communication is a good instrumental variable for two reasons. First, peer firms' behavior can have a normative effect, especially given that peer firms face similar market conditions (Germann et al. 2015). Thus, the instrumental variable is relevant. Moreover, in our analysis, a large number of firms form the group of peer firms for a focal firm. As such, it is unlikely that the average behavior (e.g., social media communication) of these firms correlates with firm-level omitted variables that can impact a focal firm's performance (e.g., organizational culture; Germann et al. 2015). As such, the proposed instruments should meet the exclusion restriction.

In the first stage of the control function approach, we estimated the following two equations:

(3) $$\text{Impersonal}_{it} = \beta_{01i} + \beta_{11}\text{Ave\_Impersonal}_{it} + \beta_{21}X_{1it} + \mu_{1it}$$

(4) $$\text{Personalized}_{it} = \beta_{02i} + \beta_{12}\text{Ave\_Personalized}_{it} + \beta_{22}X_{2it} + \mu_{2it}$$

In these equations, β_{01i} and β_{02i} represent firm-specific heterogeneity with regard to impersonal and personalized communication, respectively. β_{11} and β_{12} capture the impact of industry's average impersonal and personalized communication. β_{21} and β_{22} capture the effects of a vector of control variables which includes industry-level controls (competitive intensity, and industry size), firm-level controls (Advertising intensity, R&D intensity, leverage, organizational slack, cost of goods sold, and return on assets), and tweet-level control (average length of tweets), as well as quarter dummies. Finally, μ_{1it} and μ_{2it} are random error terms. We then estimated eq. (5). This equation is identical to eq. (2), the exception being that it includes the two predicted residuals from eq. (3) and eq. (4). The effect of these predicted residuals is captured by vector δ.

(5) $$\text{TOBINQ}_{it} = \alpha_0 + \alpha_1\text{Impersonal}_{it} + \alpha_2\text{Personalized}_{it} + \alpha_3\text{ImpersonalPersonalized}_{it} + \alpha_4X_{it} + \delta\mu_{it} + \epsilon_{it}$$

The results of stage one and two are presented in Tables 3 and 4, respectively. These results indicate that our findings remain qualitatively robust after accounting for the effect of the control function correction on performance, which mitigates endogeneity concerns. Specifically, there is a statistically positive association between impersonal communication and firm performance and between personalized communication and firm performance. Also, the interaction term is negative and statistically significant. All of these results are consistent with those reported in Table 2.

To further address the endogeneity concern, we relied on the panel nature of the data which enables utilizing panel internal instruments. We re-estimated our model using the Arellano-Bover/Blundell-Bond system of generalized method of moments (SGMM) estimator (e.g., Arellano and Bond 1991). This method, which yields unbiased estimates, is useful in the current context as it deals with panels with small *T* (i.e., few time periods) and large *N* (i.e., many firms), as well as heteroskedasticity and auto-correlation (Roodman 2009; Rego et al. 2013). SGMM is based on the idea of using lagged differences and levels of the endogenous variable(s) as instruments, which makes it possible to account for unobserved heterogeneity and address potential sources of endogeneity without necessitating the existence of strictly exogenous instruments (Chung 2015). In other words, SGMM estimations are unbiased (e.g., consistent) and efficient in the presence of endogenous variables, as well as fixed effects.

We treated the two modes of communication and their interaction as endogenous covariates and conducted a two-step SGMM model to obtain heteroskedasticity- and autocorrelation-robust estimates, as well as robust standard errors to correct for the possible bias in estimating standard errors. SGMM utilizes a system of two equations, the first of which is the level equation. The second equation is transformed by first-differencing the variables in the first equation (note that first-differencing eliminates possible fixed-effects). The model then uses the lagged differences and the levels of the endogenous variables as instruments for the equation in levels and the equation in first differences, respectively. An important step in setting up the SGMM model is specifying the appropriate lag length for the instruments. This is important because the existence of autocorrelation can make some lags invalid as instruments (Roodman 2009). More specifically, when AR(X) is not significant, the X^{th} and deeper lags of the endogenous variables can be used as instruments in the transformed equation. Accordingly, we tested for the presence of AR (2) in the transformed equation.

The results indicated that there is no serial correlation in the second-differences of the residuals (Arellano-Bond test: $z = –0.19$, $p > 0.10$). To further test the validity of the instruments, we conducted a Hansen's test of over-identification restriction, as well as a difference-in-difference Hansen's test of exogeneity. The former failed to reject the null hypothesis that the instruments are orthogonal to the error terms (χ^2 (80) = 78.79, $p > 0.10$). The latter failed to reject the null hypothesis that the subsets of instruments used in the level equations are exogenous (χ^2 (62) = 63.37, $p > 0.10$). Together, these results indicate that the instruments are valid, and the model's specification is correct. The results of the SGMM estimation, presented in Table 4, is similar to the previous estimations, providing further support for our findings.

Finally, to test the generalizability of our sample, we conducted a two-sample mean difference t-test between our sample and the other S&P 500 firms (e.g., Feng, Morgan, and Rego 2017). The results suggest that there is no significant difference between the two groups in terms of their R&D intensity, leverage, organizational slack, cost of goods sold, and return on assets.

2.6. Further Analysis: A More Fine-Grained Categorization of Tweets

Our results indicate that, although a firm's impersonal and personalized communications on social media both have a positive association with firm performance, they suppress the impact of each other. As mentioned before, our measure of impersonal communication includes any tweet that is not personalized for a specific user (i.e., does not contain a username at the beginning). Following past categorizations of firm communication on Twitter (e.g., Hewett et al. 2016; Boyd et al. 2010), we further classified impersonal communications into original tweets and retweets (tweets containing any form of the letters "RT" at the beginning). In order to further explore the impacts of firms' social media communications, we broke down our measure of impersonal communication into these two categories and estimated eq. (6).

$$TOBINQ_{it} = \alpha_0 + \alpha_1 Original_{it} + \alpha_2 Retweet_{it} + \alpha_3 Reply_{it} + \alpha_4 OrigRetw_{it} + \alpha_5 OrigReply_{it} + \alpha_6 RetwReply_{it} + \alpha_7 X_{it} + \epsilon_{it} \tag{6}$$

In this equation, α_1 - α_3 represent the main effects of a firm's original tweet, retweet, and reply to another's tweet, respectively. α_4 – α_6 represent the three interactions among the communication modes. α_7 captures the impact of the same control variables as in previous models. Based on our theorizing, supported in the main study, regarding the differential nature of impersonal and personalized communication, we predicted that each of these communication types is positively associated with firm value. Furthermore, we predicted a positive interaction between tweeting and retweeting, and a negative interaction between tweeting and replying, as well as between retweeting and replying.

The results, presented in Table 5, present an interesting pattern. According to these results, tweeting and replying are positively associated with firm performance. By contrast, retweeting has no significant impact on firm performance. Moreover, retweeting does not have a significant interaction with tweeting, but it does weaken the impact of replying on firm performance, consistent with the finding from our main analysis. Finally, tweeting and replying weaken the positive impact of each other on firm performance, as reflected in the negative interaction. These findings provide a more fine-grained picture of how different modes of communication impact firm performance. One possible explanation for the lack of effectiveness of retweeting could be consumer skepticism (e.g., Escalas 2007). Firms mainly employ retweeting to share positive publicity (e.g., other customers' positive experience with the brand) with their target audience (Burton and Soboleva 2011). However, consumers have the tendency to believe that firms use tricks to persuade them (e.g., Goh et al. 2013). This general skepticism could decrease the effectiveness of retweeting, as consumers may assume that firms are selective in what they retweet. One could argue that the same reasoning potentially applies to tweeting. In their original tweets, however, firms usually communicate objective, firm-related information such as offerings, prices, and promotions (e.g., Risius and Beck 2015; Mandviwalla and Watson 2014), and not just promotional contents. This might explain why tweeting might be more (though perhaps not fully) immune to consumer skepticism.

2.7. Discussion

2.7.1. Summary of Findings

The emergence of social media has considerably changed how firms communicate with their audience. Social media has enabled firms to forge stronger connections and deeper interactions with their customers. It has, however, added to the complexity of firm communication (e.g., Gensler et al. 2013). The current research explores this complexity by building on the literature about firms' social media communication, as well as integrated marketing communication. Specifically, we compile a dataset including the tweets of 375 S&P 500 firms, as well as data from *COMPUSTAT* and Kantar Media's Ad$spender, to study how different modes of communication on social media (impersonal and personalized) interact in impacting firms' financial performance. According to the results, impersonal and personalized communication both have a positive direct effect on firm performance. However, this study paints a more intricate picture, showing that each mode of communication diminishes the impact of the other.

To extend the findings further, we then break down impersonal communication on Twitter into its two components: original tweets and retweets. We find that the impact of impersonal communication is driven mainly by original tweets. Specifically, we find that while tweeting and personalized communication (i.e., replying) are both positively associated with firm performance, retweeting has no significant impact. Retweeting does, however, weaken the impact of replying (but not of tweeting) on firm performance. Similarly, tweeting and replying weaken the positive impact of each other on firm performance.

2.7.2. Theoretical Contribution

Our findings make several contributions to the literature. First, this research adds to the growing literature on firms' social media communication, a topic that is still relatively underexplored. Given the importance of exploring the financial value of social media communication, there have been calls for research on this topic (e.g., Luo et al. 2013). Responding to these calls, the current work reveals a positive association between social media communication and firm financial performance. In this way, the current work provides extra evidence for the idea that firms should actively engage with social media and underscores the benefits associated with an active social media presence.

Relatedly, the current work addresses an important gap in the literature. Specifically, despite its importance, research on the impacts of a firm's different social media communication modes still lags (Goh et al. 2013). The current work is, then, unlike previous research, which has mostly explored either the aggregate impact of firm communication on social media or merely the impact of impersonal communication (e.g., Kumar et al. 2016; Miller and Tucker 2013). Our study distinguishes between two modes of communication and demonstrates the positive association of each with firm performance.

We attribute the positive impact of impersonal communication to its informational value (e.g. reducing consumers' and investors' information asymmetry, building brand image), and the positive impact of personalized communication to its role in improving a firm's social capital, both of which can improve consumers' satisfaction. Specifically, as a firm's social performance measures (e.g., its relationship with stakeholders) are often uncertain and ambiguous to general investors (Luo et al. 2015), and as investors have limited attention (e.g., Hirshleifer and Teoh 2009), visible signals such as social media activity can have a significant impact on investors' decisions (Luo et al. 2013). Our theorizing and findings are also consistent with theories of market-based assets (Srivastava, Shervani, and Fahey 1998), which find that marketing activities can generate market-based assets, which can, in turn, increase shareholder value.

The mentioned distinction also enables the current research to go beyond main effects to explore the interrelated impact of impersonal and personalized communication, thus offering a more detailed account of the financial value of these communication modes. The findings show that the effects of communication modes are more intricate than a sole focus on the main effects would suggest. In revealing the suppressive impact that each communication mode has on the other, this research refines our understanding of the performance implications of firm communication on social media. Indeed, perhaps the most important characteristic of social media is that it has enabled firms to engage in one-on-one communication with their target audience (e.g., Hewett et al. 2016). Accordingly, researchers have encouraged firms to engage in personalized communications with customers, assuming that this will improve the benefits associated with their social media presence (e.g., Goh et al. 2013). For example, Luo et al. (2013) argue that any investment in processes that increase a firm's online interaction with its customers may create intangible assets.

Consistently, empirical findings corroborate this idea, highlighting that personalized communication can have even higher payoffs compared with impersonal communication (e.g., Goh et al. 2013). Although the current work does not refute this idea and, in fact, supports it, it does reveal an intricate interplay between different modes of firm communication and argues that neglecting the interactive impact of them can result in misleading conclusions. This finding might help explain why the effectiveness of firms' social media communication practices differ (e.g., Swayne 2015; Hewett et al. 2016). Although past research has suggested that a conflict between different communication modes of a firm on social media may be a possibility (e.g., Huang et al. 2015), the current work is, to the best of our knowledge, the first to explore this idea empirically.

The current work also adds to the literature on firm communication through social media by breaking down impersonal communication on Twitter into its two components—tweeting and retweeting. The negative interaction between tweeting and replying, as well as between retweeting and replying, provides further support for our theory: because impersonal and personalized communications can convey inconsistent and even conflicting messages, they can negatively impact each other's effectiveness. By contrast, because both tweeting and retweeting are under a firm's control, the risk of conflicting messages is lower, as evidenced by the lack of interaction between the two. Last but not least, unlike many past studies which has either studied one firm (e.g., Goh et al. 2013) or one industry (e.g., Hewett et al. 2016; Luo et al. 2013), this research explores the impact of the social media communications from a large sample of firms across a wide range of industries. This increases the external validity of the findings.

2.7.3. Managerial Implications

One of the challenges for firms in developing their social media strategy is a lack of sufficient understanding of the various aspects of communication in this medium. Despite the upward trend in firms' investment on social media, there is heterogeneity in how different firms communicate on these platforms: Some view social media as a broadcasting medium, while others see social media as a vehicle for personalized communication (Hewett et al. 2016). Moreover, there is evidence of varying effectiveness of social media communication practices among the firms, even within the same industry (e.g., Swayne 2015; Hewett et al. 2016). We believe that the lack of clarity regarding how different modes of social media communication interact in affecting firm outcomes might be one reason for this heterogeneity.

Our work informs practitioners that, although the ability to engage in both impersonal and personalized communication on social media is potentially a blessing, it can have significant risks. Perhaps the most important take-away here is that a compartmentalized view of different communication modes can be detrimental to the effectiveness of a firm's social media presence. When formulating their social media strategy, executives need to have an integrated perspective and consider different modes of communication as parts of a unified system. In this regard, there seem to be two important considerations. First, executives need to keep in mind the important tension between communication modes: impersonal and personalized communication weaken the impact of each other. This highlights the need for balancing the use of communication modes in such a way that maximizes the total impact of social media communication on firm performance.

Moreover, firms need to proactively try to mitigate the suppressive effect between impersonal and personalized communication. One possible strategy would be using multiple firm-sponsored accounts. This means that firms can have an account mainly dealing with customer service (given that a major part of firms' personalized communication is related to customer service; e.g. Hewett et al. 2016), and another related to promotional and informational purposes. This strategy might mitigate the suppressive impact of communication modes by decreasing the *reach* of information that are irrelevant to the broad audience, as well as information that are inconsistent with the image the firm tries to promote, since many followers, as well as casual visitors, might be less likely to follow the *customer-service account*.

Aside from using multiple accounts, another important strategy could be consistency across communication modes. Maintaining strategic consistency of communication across campaigns and mediums remains a challenging task for firms (Joo et al. 2013), and success stories are not prevalent (Gensler et al. 2013). There is evidence that firms' communication on social media suffers from the same problem (e.g., Hewett et al. 2016; Burton and Soboleva 2011). Recognizing the risk of inconsistency in social media communications, some firms only respond to positive customer communication, and some do not engage in personalized communication at all. We argue, however, that an effective strategy might be decreasing the promotional language of impersonal communication and thus making it more moderately toned. Such a strategy might decrease the thematic gap between personalized and impersonal communication, thus decreasing the suppressive effect.

2.7.4. Limitations and Directions for Future Research

The limitations of this study offer several avenues for further research. First, our sample includes established firms listed in the S&P 500 stock market index. The fact that our sample's firms represent a wide range of industries gives some confidence in the generalizability of the results to other large-cap companies. Future research, however, can further enhance the generalizability of the findings by exploring how different modes of communication impact younger firms (e.g., new ventures), since early stage firms differ from established firms in many ways, including their organizational objectives (e.g., legitimacy, fundraising) and their target audience (e.g., venture capital firms; Fischer and Reuber 2011).

Similarly, heterogeneity could exist with regard to how social media communication affects B2B versus B2C firms, since the former mainly serves organizational customers and the latter interacts with end users. Due to such inherent differences in their customer bases, B2B and B2C firms may employ distinctive communication styles.

In addition, given that in this study social media data was crawled from Twitter, it was not possible to collect all of the user-generated tweets that mentioned the focal firms' Twitter handle. Firms often don't respond to all of the tweets that mention them, however they vary widely in terms of how reactive (to user-generated tweets that have a bearing on them) they are. Future research can explore the impact of this important variable, by employing a data set which includes the quantity of firm-related user-generated tweets.

Finally, the focus of this investigation has been limited to firms' communication on Twitter. Given the differences between Twitter and other social networks (such as Facebook), future research can expand the scope of the study by investigating firms' communication on other social media platforms.

Tables of Chapter 2

Table 1: Descriptive Statistics

	Mean (S.D.)	1	2	3	4	5	6	7	8	9	10	11	12
1. Impersonalized communication	161.52 (192.87)												
2. Personalized communication	59.55 (163.43)	0.19***											
3. Average tweet length	12.67 (1.85)	-0.07***	0.19***										
4. Cost of goods sold	3486.21 (6546.64)	0.007	0.04*	0.03									
5. Advertising expenditures	0.01 (0.02)	-0.04*	0.04*	0.07**	-0.05*								
6. Industry competitiveness	0.84 (0.22)	-0.03	0.00	0.07***	-0.08***	-0.01							
7. Financial leverage	0.24 (0.16)	-0.1***	-0.04*	0.04*	-0.11***	0.00	0.00						
8. Organizational slack	0.06 (0.06)	0.03	0.03	-0.1***	-0.02	-0.03	0.03	0.01					
9. Industrial size	77070.67 (131883.8)	0.03	0.05**	0.15***	0.34***	-0.07**	0.29***	-0.19***	-0.12***				
10. R&D expenditure	136.46 (474.85)	-0.01	-0.01	0.01	0.03	0.01	-0.03	0.00	0.18***	0.00			
11. ROA	0.01 (0.02)	0.05	0.03	-0.08***	-0.05*	-0.02	-0.1***	-0.11***	0.33***	-0.13***	0.01		
12. Tobin’s q	2.17 (1.38)	0.02	0.02	-0.13***	-0.15***	0.12***	-0.04*	-0.04	0.32***	-0.2***	-0.08***	0.33***	

* *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001

Table 2: Effects of Impersonal and Personalized Social Media Communication on Firm Performance

DV= Tobin's q	**GLS** **Model 1**	**GLS** **Model 2**	**GLS** **Model 3**
Impersonal communication		0.024*** (0.003)	0.03*** (0.004)
Personalized communication		0.023*** (0.006)	0.052*** (0.009)
Impersonal*Personalized			-0.023*** (0.006)
Average tweet length		-0.047*** (0.005)	-0.047*** (005)
Cost of goods sold	-0.038*** (0.004)	-0.041*** (0.004)	-0.041*** (0.004)
Advertising expenditures	0.065*** (0.012)	0.09*** (0.05)	0.084*** (0.015)
Industry competitiveness	-0.045*** (0.005)	-0.042*** (0.006)	-0.043*** (0.006)
Financial leverage	-0.028*** (0.006)	0.001 (0.007)	0.001 (0.007)
Organizational slack	0.14*** (0.008)	0.165*** (0.009)	0.167*** (0.009)
Industrial size	-0.145*** (0.006)	-0.122*** (0.006)	-0.122*** (0.006)
R&D expenditure	0.005* (0.002)	0.003 (0.003)	0.003 (0.003)
ROA	0.098*** (0.008)	0.097*** (0.009)	0.098*** (0.009)
Wald's χ^2	3374.7	4811.9	23,981.6
N	2948	2948	2948

** p < 0.05, ** p < 0.01, *** p< 0.001; Standard errors of coefficients of estimates are presented in parentheses.*

GLS estimation with corrections for panel-specific AR1 and heteroscedasticity is used.

The coefficients of dummy variables are excluded for brevity.

Table 3: Robustness Checks (Addressing Endogeneity): Control Function Approach, First Stage

	DV: Impersonal communication	DV: Personalized communication
Industry average	0.081** (0.027)	0.052* (0.024)
Average tweet length	-0.003 (0.031)	0.064 (0.039)
Cost of goods sold	-0.097 (0.083)	-0.05 (0.104)
Advertising expenditures	0.083 (0.075)	-0.026 (0.094)
Industry competitiveness	-0.083 (0.095)	-0.09 (0.119)
Financial leverage	-0.083 (0.072)	-0.009 (0.09)
Organizational slack	-0.035 (0.038)	-0.041 (0.048)
Industrial size	-0.033 (0.042)	-0.007 (0.053)
R&D expenditure	-0.012 (0.018)	-0.019 (0.023)
ROA	-0.014 (0.029)	-0.021 (0.037)

** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors of coefficients of estimates are presented in parentheses.*

The coefficients of dummy variables are excluded for brevity.

Table 4: Robustness Checks (Addressing Endogeneity): Second Stage Control Function Approach, and SGMM

DV= Tobin's q	Control function approach	SGMM
Impersonal communication	0.05*** (0.009)	0.117* (0.057)
Personalized communication	0.076*** (0.011)	0.185* (0.088)
Impersonal*Personalized	-0.013* (0.006)	-0.206** (0.076)
Average tweet length	-0.063*** (0.006)	0.057 (0.121)
Cost of goods sold	-0.05*** (0.007)	-0.052 (0.031)
Advertising expenditures	0.243*** (0.022)	0.068 (0.037)
Industry competitiveness	-0.011 (0.006)	-0.042 (0.039)
Financial leverage	-0.018* (0.007)	-0.002 (0.034)
Organizational slack	0.208*** (0.01)	0.309*** (0.048)
Industrial size	-0.114*** (0.006)	-0.073*** (0.019)
R&D expenditure	0.005 (0.003)	-0.012 (0.01)
ROA	0.11*** (0.009)	0.175*** (0.041)
Impersonal communication (Residual)	-0.056*** (0.01)	
Personalized communication (Residual)	-0.052*** (0.009)	
Wald's χ^2		211.6
N	2948	2948

** p < 0.05, ** p < 0.01, *** p< 0.001; Standard errors of coefficients of estimates are presented in parentheses.*
The coefficients of dummy variable are excluded for brevity.

Table 5: The Impacts of Different Types of Tweets on Firm Performance

DV= Tobin's q	GLS
Tweeting	0.014* (0.006)
Retweeting	0.003 (0.007)
Replying	0.054*** (0.008)
Tweeting*Retweeting	0.004 (0.007)
Retweeting*Replying	-0.01** (0.003)
Tweeting*Replying	-0.013*** (0.003)
Average tweet length	-0.048*** (0.005)
Cost of goods sold	-0.039*** (0.005)
Advertising expenditures	0.086*** (0.015)
Industry competitiveness	-0.044*** (0.006)
Financial leverage	0.003 (0.007)
Organizational slack	0.167*** (0.009)
Industrial size	-0.116*** (0.006)
R&D expenditure	0.004 (0.003)
ROA	0.093*** (0.009)
Wald's χ^2	2628.95
N	2948

$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$; Standard errors of coefficients of estimates are presented in parentheses.

GLS estimation with corrections for panel-specific AR1 and heteroscedasticity is used.

The coefficients of dummy variables are excluded for brevity.

Figures of Chapter 2

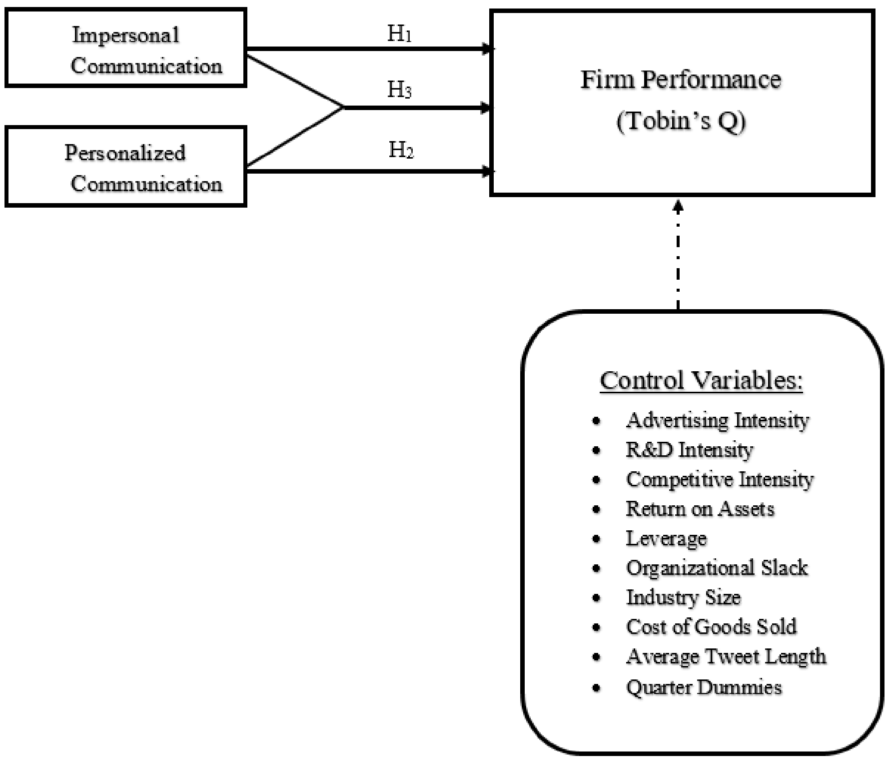

Figure 1. Conceptual Framework

Appendix: Summary of Variable Operationalization and Data Sources

Variable	Operationalization	Source	Type of analyses*
Tobin's Q	(market value of common stock shares + book value of preferred stock + book value of long-term debt + book value of inventories + book value of current liabilities – book value of current assets)/(book value of total assets)	*COMPUSTAT*	Main
Impersonal Communication	The quarterly count of tweets that don't contain a username at the beginning (i.e., tweets that don't address an individual user).	*Twitter*	Main
Personalized Communication	The quarterly count of tweets that contain a username at the beginning (i.e., tweets that address an individual user).		Main
Original tweets	The quarterly count of original tweets (tweets that are neither retweet, nor reply)		Alternative
Retweets	The quarterly count of retweets (tweets containing any form of the letters "RT" at the beginning)		Alternative
Replies	The quarterly count of tweets that contain a username at the beginning (i.e., tweets that address an individual user).		Alternative
R&D intensity	Total R&D expenditures scaled by sales	*COMPUSTAT*	Main
Competitive intensity	Reciprocal of the Hirschmann–Herfindahl index		
Return on assets	Income before extraordinary items scaled by total assets		
Leverage	Long-term debt scaled by total assets		
Organizational slack	Ratio of net cash flow from operating activities scaled by total assets		
Industry size	Total sales of all firms in the same industry		
Cost of goods sold	-		
Average length of tweets	-		
Advertising intensity	Advertising expenses scaled by sales	Ad$*spender and COMPUSTAT*	

**Main variables are used in the main analysis. Alternative variables are used in further analysis.*

CHAPTER 3

Essay 2: How Social Media Communication Can Drive Venture Capital Funding

Abstract

New B2B ventures' (NB2BVs) success is tied to their ability to differentiate themselves from their competitors, and their potential for successful collaboration and value co-creation with customers. However, little research has explored how NB2BVs can impact investors' decision by signaling these qualities. Building on the literature about signaling theory, value co-creation and differentiation, as well as the related literature about comparative linguistics, the current work argues that the extent of lingual similarity of a NB2BV's social media communication to that of their competitors and potential customers can communicate signals about these qualities, thus impacting investors' funding decision. The study is based on a unique dataset compiled through longitudinal tracking of the tweets of 382 B2B new ventures (B2BNVs) across multiple fundraising stages and data on their raised financial capital. The results indicate that lingual similarity of a NB2BV's tweets to its potential customers' tweets, and their lingual dissimilarity to competitors' tweets, signal its potential for successful value co-creation and differentiation capabilities, respectively, with both aspects increasing the success in fundraising. Moreover, NB2BVs that concurrently maintain a similarity to customers' tweets and dissimilarity to competitors' tweets are more successful in raising funds than the ones that can attain only one of these goals. These findings are robust to alternative analyses and measures.

***Keywords*:** Value Creation, Value Appropriation, Marketing Ambidexterity, Social Media, Lingual Similarity.

3.1. Introduction

An important aspect of the marketing function in an organization is comparatively situating the organization among other relevant organizations. Importantly, B2B firms, with a complex organizational landscape that entails a concurrent presence of competitor and customer firms[9], need to: a) differentiate themselves from their competitors, reflecting on their potential to compete (e.g. Ulaga and Eggert 2006); and b) relate themselves to their customers, reflecting on their potential for successful collaboration and value co-creation with customers (e.g. Coviello et al. 2002).B2B firms can pursue these goals through their communications. For instance, through advertising campaigns, B2B firms can emphasize aspects of their product that differentiate them from competitors. Similarly, they can show their commitment to aspects of business that matter for their customer firms. While the traditional communicative means of differentiation from competitors and relating to customers (e.g., advertising campaigns) are at established firms' disposal, new B2B ventures (NB2BVs) can rarely benefit from such means, as they lack sufficient structural, and financial capital (e.g. Bresciani and Eppler 2010). However, ubiquity, reach, and low costs of social media present an opportunity for NB2BVs to access an effective platform of communication.

In spite of the promise of social media as a communication platform for NB2BVs to situate themselves in their organizational fabric, empirical evidence regarding the effectiveness of such platforms for this purpose is lacking. More generally, while the role of social media in promoting a company's message amongst its micro-customers (e.g. an airline communicating with passengers) is relatively well-versed (e.g., Kumar et al. 2016), their role in providing a platform for positioning a firm relative to the customer and competitor firms is less understood.

[9] Unlike B2C firms that mainly engage in organizational discourse with firms that are competitors.

Specifically, for NB2BVs, with their complex organizational landscape (i.e., a mix of competitor and customer firms) and limited means to engage in other forms of organizational communication, understanding this distinct role of social media is of a paramount importance.

We make sense of a NB2BV's relative situation to its related organizations by focusing on the lingual similarity and dissimilarity of its social media communications to those of its customers and competitors, respectively. We build on the literature about signaling theory, value co-creation and differentiation, as well as the related literature about comparative linguistics (Johnson et al. 2014; Hollingshead 2011; Wickham and Walter 2007; Yoo and Alavi 2004), and assess the *topic* and *sentiment* content of a NB2BV's communications, as well as their *complexity*, relative to those of its customers and competitors.

Specifically, we contend that lingual *dissimilarity* to competitors signals a NB2BV's potential to differentiate itself from competitors, whereas its lingual *similarity* to customer firms signals a greater alignment between the NB2BV and its potential customers, increasing the possibility of a collaborative relationship. As research shows, collaboration is crucial for B2B value creation (e.g. Dotzel and Shankar 2016) and thereby, such similarity can signal greater potential for value co-creation.

Since capital funds raised from external investors is new ventures' indicator of market valuation and key to their future growth (Zimmerman and Zeitz 2002), and also because differentiation from competitors and co-creating value with customer firms is essential to the success of B2B firms (e.g. Aarikka-Stenroos and Kaakkala 2012; Noordhoff et al. 2011), the study predicts, based on the above theoretical argument, that *lingual similarity(dissimilarity) to customers (competitors) of a NB2BV should positively affects its success in raising capital funds.*

To test these ideas, we draw upon multiple sources (e.g., angel.co, COMPUSTAT, LinkedIn, and *Twitter*) to compile a dataset by longitudinally tracking the tweets of 382 NB2BVs active in the area of software-as-a-service (SaaS) over multiple stages of their fundraising and integrating it with data on the financial capital raised by the ventures. Specifically, we focus on *Twitter* as the social media platform used by new ventures to engage in organizational communication following empirical evidence that suggests new ventures strategically leverage *Twitter* to broadcast their organizational messages[10] (e.g. Fischer and Reuber 2014).

Analyzing the topic, sentiment, and complexity aspects of the social media communication by NB2BVs, their competitor, and their customers, we demonstrates that lingual similarity (vs. dissimilarity) of a B2BNV's tweets to those of its customers (vs. competitors) is positively associated with its success in fundraising. Furthermore, we show that NB2BVs that can concurrently maintain a similarity to their customers and dissimilarity to their competitors are more successful in raising funds than the ones that can only achieve one of these two goals. The results further indicate that a one standard deviation *increase* in lingual similarity to customers is associated with nine percent increase in the raised capital in each round, and a one standard deviation *decrease* in lingual similarity to competitors is associated with almost ten percent increase in the raised capital.

The rest of the paper is organized as follows. First, we review the relevant literature on value co-creation, and differentiation as two core capabilities that influence the success of NB2BVs. Then, building on signaling theory as the theoretical lens, we develop our arguments about how social media communications can signal these capabilities. Thereafter, we describe

[10] We note that other platforms such as Facebook are also used to engage in environment, however, use of *Twitter* for broadcasting organizational messages is more accepted, whereas platforms with more distinct features for synchronous communication, such as Facebook, are more utilized for interactive relationships rather than broadcasting firm identity and its core messages.

the empirical methods and present the results. The paper concludes with a discussion of its theoretical and managerial implications.

3.2. Theoretical Background

While B2C firms mostly face the organizational environment that is consisted of some competitors and, in some cases, few allies, the organizational landscape of B2B firms is representative of a more balanced mix where both business partners (i.e., organizational customers) and competing firms are relevant and actively presented. In order to create sustainable competitive advantage in such a two-sided organizational environment, B2B firms need to: a) differentiate themselves from their competitors, reflecting on their potential to compete (e.g. Ulaga and Eggert 2006); and b) relate themselves to their customers, reflecting on their potential for successful collaboration and value co-creation with customers (e.g. Coviello et al. 2002).

Given the role of these capabilities in a B2B firm's success, investors may also pay attention to these qualities when making investment decisions. Importantly, given the lesser known potential of NB2BVs to survive in a market's environment, signals of their potential to co-create value with organizational customers, and to compete with competitors might impact NB2BVs' success in the crucial task of fundraising. The current work argues that a NB2BV's communication can impact investors' sensemaking about its plausibility, by signaling its potential for successful value co-creation and differentiation. Importantly, we reveal the importance of the signals sent through social media in influencing investors, given the ubiquity, reach, and low costs of these platforms and NB2BVs' lack of sufficient structural, and financial capital to utilize the traditional means of communication. Next, we review, in greater detail, vale co-creation and differentiation, as two capabilities that impact business performance and lay out our arguments regarding the role of social media in signaling them.

3.2.1. Value Co-Creation: An Important Aspect of Value Creation

Strategy literature highlights the importance of value-adding activities as a source of profitability and market success for firms (e.g., Porter 1985). According to this view, one strategic consideration for any firm is to figure out how to create superior value for its customers (Aspara and Tikkanen 2013). Consistent with this idea, the marketing strategy literature identifies product innovations resulting from research and development activities as the main source of value creation (e.g., Swaminathan et al. 2008). The created value can extend the demand boundaries and reduce a firm's cash flow vulnerability (Srinivasan et al. 2009), contributing to the firm's long-term profitability (Moorman and Miner 1997).

Value creation is even more important for new ventures. Indeed, research shows that value creation through innovation is an important ingredient for new ventures' legitimacy and success (Song et al., 2008). Capital gains realized through innovation not only increase the wealth of investors, but also signals their investment success, enabling them to attract better quality ventures in the future (Gompers and Lerner, 2004, Park and Steensma 2013). Given the importance of value creation, it is no surprise that stakeholders and investors pay considerable attention to new ventures' *potential* for *successful* value creation, especially given the inherent risk involved in value creating activities (e.g., Rao et al. 2008). As Park and Steensma show, "corporate investors tend to fund new ventures with greater pre-funding innovative capabilities" (2013, p.311).

In creating value, B2B firms differ markedly from their B2C counterparts in that they are rarely able to create value in isolation (i.e., closed innovation). In a B2B firm, value creation, which is a critical driver of success and growth (e.g. Dotzel and Shankar 2016) results from collaboration (i.e., co-innovation) with organizational customers (Wagner et al. 2010; Fang et al. 2016). As Kaufman et al. (2006) argue, interfirm collaboration has the potential for creating long term value. Although *value co-creation* also exists in the B2C context (Lusch and Nambisan 2015), interactive value creation is likely to be more important in the B2B context. In fact, joint innovation between firms and their organizational customers, wherein the two parties integrate their resources and competencies, is an increasingly popular strategy for B2B firms, at both dyadic and network levels (Noordhoff et al. 2011). Even when B2B firms and their organizational customers are not officially involved in a joint innovation, B2B firms improve their value creation capability through a relational process of building collaborative relationships with organizational customers and exchanging knowledge with them (Rindfleisch and Moorman 2001), a process that is very important given the fact that knowledge exchange has a pivotal role in B2B innovation (e.g., Carson 2007; Rindfleisch and Moorman 2001)

A collaborative relationship with customers can streamline the value creation process and increase the success chance of an innovation. The positive impacts of such relationships stem from the fact that the *long-term relationship* mindset fosters trust (Mallapragada et al. 2015), facilitating the sharing of expertise, knowledge, and resources, which could allow firms to learn from one another, thus facilitating the development of new products and services (e.g., Barrett et al. 2015). As such, B2B firms that build long-term relationships (vs. discrete transactions) with their customers are more likely to be successful in value co-creation and thus enjoy long-term benefits (Lambert and Knemeyer 2004).

In line with this notion, numerous research works have documented the positive impact of *B2B firm-organizational customer* collaborative relationships on the success of value creation activities (Wagner, et al. 2010). For instance, the literature about embedded ties (e.g., Kaufman et al. 2006; Rindfleisch and Moorman 2001) provides support for the impact of B2B close relationships (i.e., embedded ties) on value creation capabilities. According to this literature, embedded ties improve knowledge transfer between the parties, thus increasing the potential for value creation (e.g., Noordhoff et al. 2011; Rindfleisch and Moorman 2001). Similarly, research has shown that collaborative relationship with organizational customers enhance the success of major innovations by small and young B2B firms (e.g. Coviello and Joseph 2012)

In sum, the existing literature suggests that (a) in general, external entities (e.g. investors) in a firm's environment pay particular attention to its value creation capability, and that (b)collaborative relationships with organizational customers *is an important precursor of successful value co-creation*, a major aspect of value creation capability in the B2B context. However, as objective information about NB2BVs' actual ability to form successful collaborative relationships with organizational customers is not often available, the current work argues that any sign of such ability can signal the venture's potential for successful value co-creation, enhancing its perceived legitimacy, and thus, increasing its success in raising capital funds.

3.2.2. Differentiation: An Important Aspect of Value Appropriation

Although value co-creation capability is an important precursor of success, it is not the only path leading to financial profitability and market success. Indeed, research shows that value appropriation, i.e., a firm's ability to obtain, maintain, and increase benefit from the value created or accessible to it, is also an important determinant of the firm's success. Prior research shows that stock markets react favorably to an increased emphasis on value appropriation (Mizik and Jacobson 2003). According to both the resource-based view (e.g., Barney 1991), and the strategic-positioning perspective (e.g., Porter 1985), value appropriation capability enables a firm to enjoy a stable flow of profit through setting up barriers (i.e., isolating mechanisms) against competition (Aspara and Tikkanen 2013).

One of the effective value appropriation strategies is *differentiating* the firm from competitors. Indeed, according to the resource-based view, value appropriation capabilities are linked to the ownership of a scarce resource (Collis et al. 1998). For example, an increase in the reputation gap between a firm and its competitors, i.e., reputational differentiation, increases the firm's ability to command higher prices than its competitors (Obloj and Capron 2011). Similarly, owning unique market-based assets, such as a strong brand name (Lawson et al. 2012) and brand satisfaction (Lam and Shankar 2014), and successful customer relationship management (Krasnikov et al. 2009) increase the potential for value appropriation through differentiation, thus enhancing the returns from innovations. Finally, differentiation increases brand loyalty, and thus leads to better current profitability and higher residual value of the firm (Srinivasan et al. 2009).

Importantly, *differentiation* can be achieved through marketing communications. For example, advertising offers an isolating mechanism (Mizik and Jacobson 2003), because it increases a firm's reputational capital and helps the firm differentiate itself from competitors, warding off competitive initiatives (Srinivasan et al. 2009). Such a competitive power leads to better return on innovation and more stable future earnings (Srinivasan et al. 2009).

Differentiation is of paramount importance for B2B firms as well. Indeed, one of the crucial tasks of B2B marketers is to signal, through different media, a superior problem-solving capability relative to the competitors (Aarikka-Stenroos and Kaakkala 2012). Prior research offers consistent evidence that value appropriation is an important driver of business success for

NB2BVs, and that B2B firms try to differentiate themselves from competitors (e.g., Ulaga and Eggert 2006).

Given the importance of differentiation as a precursor of successful value appropriation, external entities pay careful attention to a firm's ability to differentiate itself from its competitors. For example, Frieder and Subrahmanyam (2005) show that investors have a propensity toward stocks of strong brands, even though such stocks do not necessarily outperform others in the short-term.

In sum, we have discussed value co-creation with customers and differentiation from competitors as distinct capabilities that render profit for firms, especially B2B firms. For new ventures, especially in the inception and development stages, such capabilities may have not been developed yet (e.g. Homburg et al. 2014), or at best are underdeveloped. Therefore, as NB2BVs present their business by communicating to the outside world via social media, investors may pick up signals of the venture's promise to differentiate itself from its competitors and co-create value with its customers. Below, we discuss the tenets of the signaling theory and discuss how social media may operate as a medium to signal the potential for value co-creating and differentiation to potential investors.

3.2.3. Signaling Theory

According to signaling theory, when there is information asymmetry (of varying extent) between a firm and its environment (i.e., external entities have incomplete information about the firm; Boulding and Kirmani 1993), peripheral information (i.e., signals) significantly impacts inferences derived about the firm since such information reduces uncertainty about less known attributes (Sanders and Boivie 2004). Moreover, as sources of competitive advantage in the modern marketplace shift from tangible resources to intangible knowledge-based resources, quality signals become increasingly important in evaluating firms (Sanders and Boivie 2004).

For example, prestigious top managers, firm reputation (Coff 2002), and financial statements (Zhang and Wiersema 2009) can all signal the firm's unobservable qualities to outsiders, i.e., stakeholders, customers, competitors, and potential investors.

Signaling theory is widely used in the entrepreneurship literature, where the receiver of the signal is almost always investors (Connelly, Certo, Ireland, and Reutzel 2011; Busenitz et al., 2005). The idea in this literature is that the early-stage financing market (e.g. new ventures' fundraising) is characterized by considerable information asymmetry: New ventures are unfamiliar entities, and little objective information (e.g. market-based performance measures) about their qualities are available to potential investors. As such, potential investors pay close attention to information cues (Baum and Silverman 2004; Crane 2010; Gulati and Higgins 2003), in order to reduce information asymmetry and better evaluate the potential of the new venture to fulfill their expectations about financial performance. In line with this notion, research shows that such signals of quality as top-management team characteristics, and founder involvement (Busenitz et al. 2005), positively to impact investors' decisions about new ventures.

Since marketing is critical to a new venture's success, and inefficient marketing is a major reason for a new venture's failure (Politis 2005), investors pay special attention to the new venture's marketing-related potential, and as such signaling this potential may significantly impact success in raising capital funds. For example, Homburg et al. (2014) argue that the attributes of the chief marketing officer (CMO) signal a new venture's marketing capabilities, thus impacting investors' decisions. Their results support this expectation, showing that the CMO's education, marketing experience, and industry experience are positively correlated with the odds of funding.

Although prior research has examined factors that can signal a new venture's marketing-related potential, limited attention has been given to how NB2BVs' potential for value co-creation and differentiation can be signaled. This is despite the belief that an important task for B2B firms is to signal these capabilities (Aarikka-Stenroos and Kaakkala, 2012).

More specifically, NB2BVs often exist in hypercompetitive environments, characterized by demand uncertainty and fierce competition (e.g., Grewal et al.2010), and signaling marketing potentials may be more important for them than for more established B2B firms. Addressing this gap in the literature, this paper makes the novel prediction that a NB2BV's communication on social media can signal its potential for successful value co-creation and differentiation, thus enhancing its success in raising capital.

Communication as a signaling vehicle. This paper argues that a NB2BV's communication on social media can signal important information about its potential for successful value co-creation and differentiation, thus impacting its likelihood of success in raising capital funds. This idea is based on prior literature that has discussed the potential of organizational communication in signaling key capabilities. For example, Cheney et al. (2004) point to the strategic nature of organizational communications in affecting the organizational audience as follows:

> "One dimension of rhetoric relates to the strategic function of organizational messages… 'Strategy' is a cornerstone of traditional rhetorical practice in that persuasion relies on targeted assessments of purpose, audience and message. Rhetoric, thus, seeks to have an impact beyond a self-contained effect, such as aesthetic appreciation (in poetics)." (p. 84)

Considerable prior research suggests that the *content* that is being communicated (i.e., the content of the message) can influence perceptions of the message recipient (e.g., Fischer and Reuber 2014; Martens et al. 2007). For example, highlighting such themes as relational orientation and quality (Fischer and Reuber 2014) and the pioneering nature of the firm in communications (Martens et al. 2007) can positively impact stakeholders' perception of the firm. Moreover, research has also shown that the *style* of communication (e.g., grammar, use of words) can also signal important information to message recipients. Ludwig et al. (2013), for example, have argued that similarities in the use of function words in the context of product reviews signal a common social identity, and lead to more approval and trust. They empirically demonstrated that an increased congruence between a product's online reviews and the target audience's linguistic pattern increases conversion rates.

Given the organizational landscape of NB2BVs (i.e., a mix of competitor and customer firms), the current paper argues that a NB2BV's communication should be explored vis-à-vis that of their competitors and potential customers. In so doing, we consider both the *content* and *style* of their communications. Specifically, building on the literature of comparative linguistics (Johnson et al. 2014; Hollingshead 2011; Wickham and Walter 2007; Yoo and Alavi 2004), we consider the *sentiment*, *topic*, and *complexity* aspects of the communication by NB2BVs, their competitors, and organizational customers. While the first and second aspect correspond to the *content* of communication, the third is related to the *style* of communication. First, valence, which refers to the extent to which the language used in the communication is positive or negative, is an important aspect of communication. Specifically, positivity of language used in communication, often determined by considering the collective positivity of words used in the corpus of a communication, can play a major role in the effectiveness of messages (e.g. Chevalier and Mayzlin 2006; Dellarocas et al. 2007). Second, the topics covered in messages posted in online settings have been shown to have an impact on effectiveness of online communication in contexts such as crowdfunding (Yuan et al. 2016) and market intelligence (Li and Li 2013). While different approaches such as topic modeling (e.g., Yuan et al. 2016) have been used to assess the topics covered in the corpus of a communication, bi-grams, i.e., unique combinations of two words, are frequently used (e.g., Li and Li 2013; Lo et al. 2016) as a way of identifying the theme of topics covered in a corpus. Finally, complexity corresponds to how a communicator constructs sentences (Johnson et al. 2014). It is a structural measure of the style of communication, in which texts with less syllables per word and words per sentence are considered more readable texts, and thus less complex, as they require less time to process and comprehend (Burtch et al. 2013). Research has shown that complexity is another important aspect of communication. For instance, it has been shown that the readability of a firm's communication is an indicator of its capabilities (e.g. financial capabilities; Li 2008).

While these three aspects have been considered, although most often separately, as important facets of communication in online settings, Johnson et al. (2014) suggest that considering these three aspects provides a thorough assessment of online messages. Moreover, and although at an individual level, they employed these three aspects to make comparisons between the corpus of texts generated by different agencies. Particularly, they focus on sentiment, topic, and complexity *differences* between individuals active in online discussion forums to predict the leadership role assumed by contributors to an online discussion. In this study, we build on Johnson et al.'s framework of comparative linguistics and assess the differences among messages communicated by a NB2BV and its customers, as well as competitors. In doing so, we assess the similarity (dissimilarity) of communication of a venture to its customers (competitors) by comparing the sentiment, topics covered, and complexity of messages sent by the venture and its customers (competitors). Below, we explain how similarity (dissimilarity) to the language used by customers (competitors) signal the potential of a NB2BV and encourage the potential investors to invest.

3.2.4. Signaling Value Co-creation and Differentiation Potentials on Social Media

Social media, and distinctively Twitter, have emerged as channels in which many new ventures express their identity, broadcast their core message, and intentionally or unintentionally, engage in an organizational discourse (Fischer and Reuber 2014). Communication on social media is of paramount importance for new ventures, in that they rarely employ, more traditional, marketing communication vehicles, such as TV commercials. Importantly, *Twitter* has been discussed as a channel that provide firms with opportunities to engage in symbolic actions to signal their qualities (e.g., Risius and Beck 2015). Despite this fact, little research has empirically explored how new ventures in general, and NB2BVs in particulars, can signal their potential for value co-creation and differentiation through social media.

Lingual Cues of the Potential for Value co-creation. Organizational research has highlighted the influence of inter-organizational similarity. For example, a firm is more likely to adopt outsourcing, when similar firms (in terms of ties to customers, suppliers, etc.) begin to outsource (Vitharana and Dharwadkar 2007). Importantly, research on B2B value co-creation shows that inter-organizational similarity facilitates successful collaboration. Similarity has an important position in the literature of inter-organizational collaboration. For example, Knoben and Oerlemans (2006) argue that similar organizations (e.g., in terms of culture) are more likely to have a smooth and successful collaboration. Indeed, similarity between two firms means that the pair has shared institutional logics (e.g., a common set of business and cultural assumptions and mental frameworks) which enables them to obtain a common perspective (e.g., Lounsbury and Crumley 2007), increasing the chance of the survival of their collaboration (Lusch and Nambisan 2015).

In the context of NB2BVs, this means that, the greater a NB2BV's similarity to its potential or actual organizational customers, the more likely it is to have a smooth collaboration and a successful value co-creation. Social media presents an opportunity to signal such similarity. In light of the fact that information about similarity of a NB2BV and its potential organizational customers is not readily available, we suggest that lingual similarity of the NB2BV's tweets to those of its potential customers signals a greater possibility of successful collaborative relationship and a streamlined and successful value co-creation process.

We contend that the lingual similarity of a NB2BV's social media communications (in terms of the pattern of language used) to those of its potential organizational customers can signal a shared understanding with customers and thus higher alignment between the two parties (e.g., Lusch and Nambisan 2015). A shared language facilitates communication and collaboration. Shared language is noted as one of the key determinants of knowledge sharing and knowledge transfer (e.g. Dhanaraj et al.2004). Therefore, as a NB2BV's use of language converges with its potential customers, the likelihood of smooth collaboration increases.

All three aspects of communication can bear relevance to this discussion. For instance, a NB2BV's using of the same key bigrams used by its customers shows a mutual interest in specific topics that the customer industry is focused on. Moreover, a similarity in terms of the positivity (valence) of communications indicate that the NB2BVs is aware of the tone and methods of communication that the customer industry is interested to use. Moreover, the positivity of messages sent by a customer industry may be in direct response to an event that bears relevance to the industry. As such, showing similarity in terms of positivity of language used by a supplying NB2BVs shows awareness about the event and its relevance to the customer, if not shared stakes in the event. Finally, the complexity of the language used in communications of an industry reflects on the vastness of their active vocabulary as well as the bandwidth of receivers of the message. Therefore, a NB2BV's holding to similar levels of complexity relative to its customer industry shows attention to the dominant norms and structures of the customer industry, signaling an ability to understand the customer industry and its subtle norms. Overall, NB2BVs that communicate similar to their customers signal understanding of the downstream, an ability that is key for value co-creation. Hence, we hypothesize that:

H_1: Lingual similarity of a NB2BV's tweets to those of its potential customers is positively associated with the B2BNV's success in fundraising.

Lingual Cues of the Potential for Differentiation. Based on prior literature, the greater the extent to which a firm can differentiate itself from competitors, the greater its likelihood to successfully appropriate value from the market because the differentiated identity can act as an isolating mechanism (e.g., McAlister et al. 2007; Mizik and Jacobson 2003). This notion is supported by both the resource-based view (e.g., Barney 1991), and the strategic positioning perspective (e.g., Porter 1985). Thus, B2B firms, and in particular NB2BVs, that signal higher potential for differentiation are more likely to be valued by investors, as such firms are more likely to succeed in the marketplace.

Social media can nurture signals that convey differentiation. In the current work, we argue that following distinct lingual communication patterns compared to competitors might signal a higher potential of a NB2BV to differentiate itself from competitors. This is because a distinct communication pattern could signal the presence of a different thought process, rather than competitors, that results in a focus on different topics (i.e. topic aspect), delivered in a different tone (e.g., sentiment aspect) and styles (e.g., complexity aspect). Distinguished use of language by an entity is associated with the perception of its leadership (Johnson et al. 2014). Specifically, in the inter-organizational context, distinguished communication can signal a firm's low degree of following institutional norms. When firms take a distinct topic focus, they signal attention to matters that other competitors do not or cannot target. Moreover, by taking a distinct tone (e.g., in terms of positivity of messages communicated) they can make their voice heard better among a set of harmonic messages. Also, in case the positivity of language being in direct response to an event, a distinct tone indicates a distinct set of events important to the firm, signaling its unique nature in terms of its relevance to its immediate environment. Finally, taking a distinct level of complexity signals catering to a set of audience that has a distinct bandwidth compared to what other competitors have access to. As such, we expect that such a signal will increase the chance of NB2BV's success in fundraising.

> H_2: Lingual dissimilarity of a B2BNV's tweets to those of its competitors is positively associated with the NB2BV's success in fundraising.

Lingual cues of marketing ambidexterity. Prior literature on value creating and value appropriating capabilities views them as two complementary aspects of firm strategy. For value creating activities to result in economic benefits, value appropriating activities must be pursued (Pitelis 2009). Pitelis (2009) note that:

> "Too much focus on value capture today may undermine long-term success, too much focus on value creation may deprive an organization of the means to compete and thus keep creating value. The above calls for *ambidexterity*, and the need for organizational structures, divisions of labor and vehicles that can engender value creation and value capture, exploration and exploitation, simultaneously …" (p. 1127).

Specifically, focusing solely on value appropriation can endanger the rate at which a firm innovates, endangering its long-term success (Zott and Amit 2007). Alternatively, a mere pursuance of value creation can decrease a firm's sharpness in defending its innovation in a market and appropriating its rents (O'Reilly and Tushman 2004). In addition to the theoretical arguments, empirical research shows that many firms cannot benefit from their innovations due to a dedicated focus on value creating capabilities and overlooking value appropriating ones (e.g., Golder and Tellis 1993). Specifically, after a firm creates value through innovative products or services, for it to capture the benefits of the created value, it needs to do better than its competitors which also try to take advantage (e.g., through imitation) of the firm's innovative efforts. For example, educating customers about the new product by the innovator decreases the risk of market entry for competitors (Lawson et al. 2012). Thus, competition influences the extent to which the firm can capture value. As Saloner et al. (2001) argue: "to prosper, the firm must also be able to capture the value it creates" (p. 39). Accordingly, tenets of *organizational ambidexterity* suggest that a simultaneous and coordinated pursuit of value creating and appropriating activities renders higher payoffs relative to pursuing one and abandoning the other. Ambidextrous firms are described as ones that possess the capabilities to both compete in mature markets and instigate and develop innovations.

In addition to its foundation in the general strategic management literature, the notion of ambidexterity is well accepted in the domain of marketing. Indeed, value creation and value appropriation together are called strategic marketing ambidexterity (SMA) (e.g., Josephson et al. 2016) and viewed to impact perceptions of the firms' legitimacy (Lawson et al. 2012). Marketing strategy literature considers marketing ambidexterity as an important contributor to the success of new products, and superior financial performance and firm sales (e.g., Pauwels et al. 2004).

Building on the notion of SMA and the fact that value co-creation and differentiation are important means for successful value creation and appropriation in the B2B context, we argue that a NB2BV's high lingual similarity to its potential customers, i.e., the signal of value co-creating ability, is complemented by its dissimilarity to its competitors, i.e., the signal of differentiation. NB2BVs that can pursue both directions can effectively present themselves as ambidextrous ventures that can simultaneously manage and engage in both value creating and value appropriating activities. Therefore, we hypothesize that:

H_3: Lingual dissimilarity of a new venture's tweets to those of its competitors enhances the positive effect that lingual similarity of a new venture's tweets to those of its potential customers has on the venture's success in fundraising.

3.3. Method

3.3.1. Sample and Data

Focusing on the Software-as-a-Service (SaaS) industry, as one of the most active B2B industries with an over $200 billion market size and growth projections of 18 percent in 2017 (Gartner 2017). We followed 382 new ventures that self-identified to be providing their services to other businesses (e.g., B2B) with a specific industry identified as the target customer industry[11]. Studying innovative firms in the context of B2B services is important, because there is a lack of marketing research in this area (e.g. Dotzel and Shankar 2016).

We longitudinally tracked the 382 B2BNVs from January 2012 to December 2014, where on average they experience between three to four rounds of raising capital, resulting in 1,224 venture-round observations. An average venture in this study's sample: raises $5.7 million in capital cumulatively; has between three and four co-founders; employs between 11 and 12 professionals; and was established 2.86 years prior to the data collection in January of 2012. We collected[12] information regarding capital raised in each round from the venture's profile page in *Angel.Co*, a popular online platform where new ventures present their ideas and products. The time period corresponding to each round was set to start from the time since raising funds for the

[11] While other SaaS ventures may target a general set of customers, it does not allow for evaluating lingual similarity of a focal venture with its customers as the set of potential customers to consider is unidentified or too broad. We address this shortcoming in the discussion of the study's limitations.

[12] A python engine of web scraping was designed and developed to collect information from Angel.Co, Twitter, and other related webpages.

last round ended until the date officially stated as the date for sum of funds raised for the current round (i.e., ending date of the current round). Each round on average lasts a little over 11 months. For each round of the capital-raising, we surveyed the *Twitter* page of each venture to collect tweets made by the new venture. In addition to surveying the venture's tweets, we collected tweets made by the customer industry, as well as those made by the venture's own industry. Each venture in *Angel.Co* identifies its own and customer industry by specific tags. For instance, a SaaS venture may identify itself to be active in the *cybersecurity* industry (own industry) where the *banking* industry is at the customer side. Surveying *Angel.Co*, we collected tweets by all the new ventures that had identified their business with a tag corresponding to the own industry of any of the SaaS ventures in the sample. A sample of 1,517 new ventures constituted the population of own-industry ventures (we include all 382 new ventures from the original sample here, as they compete among each other as well[13]). On average, each NB2BV was compared to 126 other own-industry ventures. Utilizing *COMPUSTAT*, and since the customer industry corporations, to the contrary of the competitor industry, are established firms, we identified and collected tweets from the established firms active in the same two-digit SIC code that correspond to the customer industry of the new ventures in the sample. This resulted in tweets collected from 1,174 firms with a *Twitter* feed available from 2012 to 2014. On average, each NB2BV was compared to 147 customer firms. Overall, 119,243 tweets from the original sample (i.e., 382 SaaS new ventures), 485,296 tweets from the own industry sample, and 335,365 tweets from the customer industry sample were analyzed (i.e., 939,904 tweets in total).

[13] This means that some of the competitors although active in the specific industry, e.g., cloud infrastructure, may not be B2B. But they are still considered competitors to the NB2BVs in our sample since customers often consider products of the industry as both services (offered by SaaS firms in the sample) and non-services.

This means that SaaS new ventures posted a tweet on average every 3.42 days, whereas this number for competing and customer firms was one tweet every 3.34 and 3.74 days, respectively.

3.3.2. Measures

We computed the *lingual similarity* of a B2BNV's tweets to the tweets of its customers (LSC) through three lingual analyses (see Johnson et al. (2015) for a thorough discussion on these three lingual aspects): syntactic (prototypicality of vocabulary; related to the topic aspect), semantic (text valence; related to the sentiment aspect), and morphological (text readability; related to the complexity aspect). Together, these aspects provide a comprehensive view of the communicative patterns that new ventures pursue on *Twitter*. The computation of these three aspects is discussed next and figure 1 summarizes their relevance to the study.

In order to assess the topic similarity of a venture's tweets to those of its customers, we adopted the statistical language modeling technique, developed by Jurafsky and Martin (2000) and calculated the word entropy between the venture's and its industry's corpus of tweets in each round to assess the syntactic similarity. To do so, we first combined the corpus of tweets belonging to a venture with the corpus of tweets belonging to the customer industry. Then, we followed a three-step approach, suggested by Johnson et al. (2015), to estimate the entropy of sentence. We did so by: a) estimating the probability of bigrams (combinations of two words) appearing in a corpus; b) estimating the probability of a sentence appearing in a corpus, by multiplying the probability of bigrams building the sentence; and c) normalizing the value obtained in step b) by taking the negative log of its probability and dividing it by the number of words in the sentence, estimating the sentence entropy. The higher the entropy of a sentence, the lower is its prototypicality to the rest of the sentences in a corpus (i.e., the sentence is more unique). We calculated the mean of the sentence entropy across all sentences comprising the tweets of a focal venture. Then, we used the inverse of the resulting value as a proxy of syntactic similarity.

For the sentiment aspect, we utilized a dictionary that identifies the polarity (i.e., weighted positivity and negativity) of English words in online settings, i.e., AFINN dictionary (Nielsen 2011), to estimate the polarity of tweets made by the new venture (sum of the polarity weights of words comprising the tweets), as well as the polarity of tweets made by other ventures in its industry to assess the semantic similarity. We used the inverse of absolute difference between these two polarity indices as a proxy of semantic similarity for each venture in each round.

Finally, we assessed the complexity similarity of a venture's tweets to those of its customers using a common measure of text readability, i.e., the automated readability index (ARI), developed by Kincaid, et al. (1975), for tweets made by each venture in each fundraising round and its customer industry's tweets in the same period. ARI considers the number of characters, words, and sentences in a corpus of text. It is computed by the following equation:

$$\text{ARI} = 4.71 * \frac{\#Characters}{\#Words} + 0.50 * \frac{\#Words}{\#Sentences} - 21.43$$

Next, we used the inverse of absolute difference between these two ARIs (new venture's and its customer industry's) as a proxy of morphological similarity.

We used the same process as above to calculate the lingual similarity of a venture's tweets to the tweets made by its own industry, i.e., by its competitors[14] (lingual similarity to own, LSO).

In the estimated models, *raised capital* in each round is treated as the dependent variable. The information about the raised capital in each round was collected from *Angel.Co*'s profile of the B2BNVs. The success of new ventures highly depends on funds they raise. Especially before

[14] We chose the "own" industry terminology so that the abbreviated terms generated for similarity to the customer and competitor industries be different. Taking that into the consideration, "own industry" and competitor industry" are interchangeable in this manuscript.

the initial public offering (IPO) and absent traditional measures of financial success, the amount of capital raised by a venture both indicates the market's evaluation of its worth and directly influences its potential success. Therefore, we use raised capital as a proxy of success for new ventures. From the conception to business planning, product development, commercialization, operationalization, expansion, and eventually public offering, new ventures raise funds from different resources. Depending on the stage of the venture's development, the fundraising round is labeled as seeding (i.e., no stage, often at the conception and research stage), Stage A, Stage B, Stage C, etc. It is possible that a B2BNV raises external funding in multiple rounds in the same stage of development. Therefore, a new venture might have two or three rounds of seeding. To operationalize a fundraising period, we focus on each round of fundraising and use the raised capital in that round as the dependent variable. Table 1 presents the correlation among the key variables in the study.

3.3.3. Controls

We control for the *stage* of development where the funding is raised because early and late stages of fundraising differ in terms of the funding providers as well as the funds needed. To best capture the effect of fundraising stage, for each stage of development (e.g., seeding, stage A, etc.) we specify a variable the value of which indicates number of fundraising rounds a new venture has completed in that stage, prior to the current round. Therefore, for B2BNVs with their first round of fundraising the value of seeding, stage A, stage B, and stage C variables are all set at 0. If a venture has had two rounds of fundraising at the seeding stage, and the current round is its second round at stage A, the value of seeding variable is set at 2, the value of stage A variable is set at 1, and the value of stage B and stage C variables are set at 0.

We also control for the *polarity* (using AFINN dictionary), *richness* of vocabulary (i.e., number of unique words used in tweets), and *readability* of tweets (ARI) made by the B2BNV in each round[15]. While some of these lingual controls are used in estimating the similarity/dissimilarity measures, we control for their level (i.e. their absolute value) to make sure that it is the relative similarity of these aspects to other firms, and not their level, that cause the observed effects. *Size* (number of employees), employees' *average level of education*[16], as well as, *location (city)*, *year*, *own* industry, and *customer* industry dummies were controlled for. A table summarizing the main measures, as well as their alternatives, is presented in the Appendix.

3.3.4. Specification

To test the direct effect hypotheses (H1 and H2) the following equation was estimated:

(1) $$Raised\_Capital_{it} = B_1*LSC_{it} + B_2*LSO_{it} + B_3*Polarity_{it} + B_4*Richness_{it} + B_5*Readability_{it} + B_6*Size_{it} + B_7*Education_{it} + Location_{it} + Own_i + Customer_i + YEAR + STAGE + \epsilon_{it} + c_i$$

Where subscripts *i* and *t* denote the *i*th venture in *t*th fundraising round. ϵ_{it} is the error term and c_i is the time-invariant unobserved heterogeneity term. To evaluate the third hypothesis, the following equation was estimated:

(2) $$Raised\_Capital_{it} = B_1*LSC_{it} + B_2*LSO_{it} + B_3\ LSC_{it}*LSO_{it} + B_4*Polarity_{it} + B_5*Richness_{it} + B_6*Readability_{it} + B_7*Size_{it} + B_8*Education_{it} + Location_{it} + Own_i + Customer_i + YEAR + STAGE + \epsilon_{it} + c_i$$

[15] We control for the polarity, readability, and richness of vocabulary used by each venture to ensure that similarity to competitors' and customers' rhetoric has an effect on the raised capital, above and beyond the effect that the content of the rhetoric has.

[16] High school diploma =1; Associate degree =2; Four-year college degree= 3; Master's degree =4; Doctoral degree =5. This information was crawled from the LinkedIn profile of the venture's founders and employees.

Before estimating models, all variables are standardized to reduce multicollinearity. Considering the panel structure of the data, and to remove the effect of the time-invariant unobserved heterogeneity term, which encapsulates factors such as an inherently superior business models or innovations owned by the new venture, a Hausman test is run in order to select the appropriate random-effects or fixed-effects model. The results of this test for the most completely specified equation (i.e., Equation 2) fails to reject the null hypothesis that the venture-level effects are adequately modeled by a random-effects model (χ^2 (43) = 7.74, $p >$ 0.10). Searching for a proper random-effects estimation, we conduct likelihood ratio tests to understand the panel-specific heteroskedasticity and the panel-specific auto-correlation structure of the data. The results of the likelihood ratio tests indicate the presence of panel-specific heteroskedasticity (LR χ^2 (43) = 305.14, $p < 0.001$), as well as panel-specific auto-correlation (PSAR1; LR χ^2 (43) = 388.81, $p < 0.001$). Accordingly, a feasible Generalized Least Square (GLS) regression with corrections for PSAR1 autocorrelation and panel-specific heteroskedasticity is used to estimate the coefficients of the proposed models.

3.4. Results

Table 2 presents the results of the analysis. Model 2.1 presents the results when the components of the LSC and LSO are independently used as covariates. The results of this model show a positive and significant effect of LSC components on the raised capital (Consistent with H1). Moreover, a consistent negative and significant effect of LSO components on the raised capital in each round is observed (consistent with H2). Due to relatively high correlations among the components of LSO, we use the arithmetic average value of the components as the measure of LSO. Similarly, due to relatively high correlations among the components of LSC, we use the average value of the components as the measure of LSC[17]. (please see Table 1). Model 2.2 presents the direct-effects model and suggests that LSC positively and significantly enhances raised capital in each round (0.079, $p < 0.05$). Moreover, LSO shows a negative and significant association with the raised capital (–0.085, $p < 0.01$). One standard deviation increase in LSC increases the raised capital by nine percent in each round, whereas one standard deviation decrease in LSO results in a ten percent increase in the raised capital. Model 2.3 presents the results of the interaction model and indicates a negative and significant interaction (–0.085, $p < 0.01$), suggesting that decreasing LSO enhances the positive effect of LSC. When LSO is low, one standard deviation increase in LSC increases the raised capital by 21 percent. Figure 2 presents the interaction plot.

3.5. Corrections for Estimate Biases

The panel structure of the dataset and the dependent variable of interest present a case where independent variables may be endogenous. This is so, because levels of LSO and LSC at round *t* can be correlated with the levels of LSO and LSC at the previous round, and by association, with the raised capital at the previous round. If the previous round's raised capital and current round's level of raised capital are correlated, an instance of reverse causality may be present. Given the unbalanced nature of the panel, as well as the presence of heteroskedasticity and auto-correlation, we utilize the Arellano-Bover/Blundell-Bond system of generalized method of moments (GMM) estimator to correct for possible biases (e.g. Arellano and Bond 1991). Specifically, this method is suitable for an unbalanced panel with a relatively large number of observations, despite the presence of independent variables that are not strictly exogenous as

[17] The components show an internal consistency of Cronbach's alpha of: 0.72 for the LSO measure, and 0.76 for the LSC measure.

well as the presence of heteroskedasticity and serial correlation (Roodman 2009). In other words, AB-GMM estimations are non-biased (e.g., consistent) and efficient in the presence of endogenous variables as well as fixed effects.

Following prior literature, we treat the LSC and LSO, and their interactions as endogenous covariates (e.g. Aral et al. 2012). Then, we conduct a two-step system GMM model to obtain estimates that are robust to both heteroskedasticity and autocorrelation and provide robust standard errors to correct for the possible bias in estimating standard errors.

The estimator employs a system of two equations. The first equation is the original (level) one, and the second equation is a transformed one that is obtained by first-differencing variables in the level equation (this equation removes fixed effects). Then, the lagged values of the endogenous variables and their differences are used as instrumental variables. In setting the two-step system, the depth of lag for instruments needs to be specified for each of the two equations. Previous studies using the same technique have relied on a Lag (2) option (e.g., Roodman 2009), which instructs the use of the second and deeper lags of the endogenous variables as instruments in the transformed equation, while the first lags of the endogenous variables are used as instruments in the level equation. In order to make sure that such specification is correct, the exogeneity of instruments and error term must be maintained, which requires that error terms are not autocorrelated. If the error terms are autocorrelated, deeper lags should be utilized in the transformed equation. We test for presence of AR (2) in the transformed equation. The results of AR (2) tests indicate there is no serial correlation in the second-differences of residuals (Arellano-Bond test: $z = -0.43$, $p > 0.10$). Further, the Hansen's test of over-identification fails to reject the null hypothesis that the instruments are orthogonal to the error terms (χ^2 (56) = 6.63, $p > 0.10$), and the difference-in-difference Hansen's test of exogeneity fails to reject the null hypothesis that the subsets of instruments used in the level equations are exogenous (χ^2 (58) = 3.36, p > 0.10). The results in Table 2 (Model 2.4) show that findings remain qualitatively robust after accounting for the threat of endogeneity by estimating Equation 2 through a two-step GMM.

Further, even though Hausman test indicates the plausibility of a random-effects model, the output of a fixed-effect estimation (Table 2, Model 2.5) converges with the main findings. Fixed effect estimations offer an alternative approach to model and remove time-invariant unobserved heterogeneity that may bias coefficient estimates. Since unobserved heterogeneity is another source of endogeneity in datasets with similar structure (e.g., Roodman 2009), fixed-effect estimates can further assure reliability of the original estimates.

In studying the effect of lingual similarity/dissimilarity on the capital raised, it is likely that the choice of making *Twitter* communication similar to customers and dissimilar to competitors is not exclusively externally driven by decision makers in NB2BVs. Rather, the level of similarity and dissimilarity to communications of other firms may depend on other external forces, such as the extent of embeddedness in the competitive or customer environment. Even though our treatment of removing unobserved heterogeneity may eliminate the effects of such external factors, the levels of similarity and dissimilarity of communication does not vary randomly in such conditions and present a case of selection bias. Garen (1984) presented an econometrics two-stage model that corrects for such a selection bias in the level of continuous (or ordinal) variables that predict a dependent variable. He suggested that the first stage should model the effect of some external variables that predict the level of the focal variable(s) (i.e., the variable(s) with selection bias). The second stage should then include the residuals from the first stage(s) in addition to the interaction of the residuals and the internally selection variable(s).

Following the recommendation of Garen (1984), we look for variables that can predict the level of similarity and dissimilarity of communication to other firms', while making sure that those predictors are not internally driven by the levels of raised capital by the new venture. As such, we focus on potential predictors that cannot be changed by levels of raised capital. One such group of predictors are those that are an inherent or a fixed aspect of a venture. Since none of the observations in our sample have changed location since inception, we believe that extent of geographical proximity to both customer and competitor firms can be a predictor of lingual similarity and dissimilarity to such firms, while at the same time such proximity is not driven by the levels of raised capital. It is so, because: a) the location of the ventures in the sample is fixed across the years of observation; and b) even if some competitors or customers move to the proximity of a focal venture, it is highly unlikely that another firm's decision to move to proximity of a venture is driven by the raised capital level of the venture. To assess geographical proximity to customers or competitors we compiled a list of all firms in 200 miles radius of a NB2BV in our sample, by searching through the firms listed in COMPUSTAT, as well as ventures listed in Angel.co. Then, from this broad list we estimate the ratios of firms that are in proximity of the focal venture and are also included in the study's sample of customer and competitor firms of that ventures. This yields two ratios, customer and competitor proximity, one corresponding to the geographical proximity to customers (as the ratio of neighboring firms that are considered to be customers) and one corresponding to the geographical proximity to competitors (as the ratio of neighboring firms that are considered to be competitors). These proximities predict the level of lingual similarity to customer and competitor firms because geographical proximity can cause a flow of work force between the venture and its customers or competitors, as well as attending to venues that customers or competitors can access. Such a flow of work force and access to shared venues can make a focal venture better aware of topics, tone, and complexity of language used by customer of competitor firms, positively influencing similarity to customers and competitors.

Another potential predictor of similarity of communication to customer and competitor firms is the extent of knowledge that founders of a focal venture have about competitor and customer firms. To assess the founders' knowledge of customers and founders' knowledge of competitors, we considered the resumes of founders posted on LinkedIn pages of founders of the ventures in the sample, and estimated the ratio of educational or professional lines in the resume of all co-founders that relate to customer and competitor industry, respectively. For instance, if a NB2BV indicates banking as the customer industry and of the ten lines in the professional and educational resumes of all co-founders there are a couple of past jobs in banking industry, the extent of founder's knowledge of customers is calculate as 2/10. Founders' knowledge of customer or competitor industry is estimated by looking at the educational and professional background of founders prior to founding the venture and thereby cannot be affected by the level of the venture's raised capital. Founders' knowledge of customer and competitor industries affects the professional venues, journals, and interests of founders, making them more similar to that of customers or competitors. Therefore, such shared understanding of customer or competitor industries can lead to greater lingual similarity to them.

Following Garen (1984) we included some of the relevant controls in the main model (i.e., the model with raised capital as the dependent variable) in the first stage models. Namely, the first stage models include number of employees, education of founders, and years since establishment in addition to the predictors mentioned above. In the second stage model (equivalent to Eq(2)) we included all variables noted in Eq(2), and in addition to that, we included the introduced variables that predict the level of similarities to customer and competitor firms, and also, included the residual term from the first stage models (ŋ's), in addition to the interaction of the residuals and similarity measures.

Table 3 presents the results of this analysis. This analysis of the first stage shows that geographical proximity to, and founders' knowledge of, customer and competitor firms significantly and positively the extent of lingual similarity to customers and competitors, respectively. Moreover, the stage 2 results show the main findings presented in previous section remain robust to additional residual terms from the stage one models. Specifically, the significance and negative sign of ŋ(Stage1A) indicates that NB2BVs that reduce their lingual similarity to competitors beyond the expected levels based on external factors, achieve higher payoffs in terms of raised capital. Moreover, significance and positive sign of ŋ(Stage1B) indicates that NB2BVs that increase their lingual similarity to costumers beyond the expected levels based on external factors, also achieve higher payoffs in terms of raised capital.

3.6. Self-Selection Bias

In selecting the new ventures for the sample, we dropped 484 observations due to the missing values for the raised capital. While the reasons for not disclosing the raised capital on Angel.Co is unclear to us, dropping those observations presents a threat of self-selection. In order to account for the potential self-selection bias, we conducted a Heckman's procedure (Heckman 1977). In doing so, we used the study's control variables, in addition to the venture's support by an incubator (1 if supported, 0 if not) and support by advisor(s) (1 if supported, 0 if not), as instruments identifying the selection factor[18]. These two additional instruments were identified through an exploratory search in descriptive variables available about the ventures in this study's sample. We conducted a Heckman's maximum-likelihood estimation in STATA while clustering the standard errors of estimates on the venture ID. Table 4 presents the results of this estimation. This estimation also shows the robustness of the findings to an alternative estimation where self-selection bias is controlled.

3.7. Alternative Measures of Independent and Dependent Variable

We further examine the sensitivity of the results by estimating the coefficients of the most specified equation (Equation 2) through alternative measures of independent and dependent variables reported in Table 5. Model 5.1 presents the coefficient estimates when the likelihood of occurrence of tri-grams (combination of three words) are used instead of bi-grams to estimate topic similarity. Moreover, while bi-grams and tri-grams are shown to be related to distinct topics in a corpus, in *Twitter*, *hashtags*, as user-defined keywords, are used to communicate key content of tweets (e.g. Nam e al. 2017). In Model 5.2, we replace our bi-gram-based measure of topic similarity with a hashtag-based measure. To do so, we first obtained the collection of hashtags used by customers (competitors) of a focal firm in tweets communicated during the focal fundraising round. Then, we estimated the proportion of these hashtags that are also used by the focal B2BNV in the same period as the measure of topic similarity to customers (competitors). Further, Model 5.3 presents the results when using an alternative dictionary, ANEW (Affective Norms for English Words; Bradley and Lang 1999), to evaluate the sentiment

[18] Angel.Co reports if a B2BNV is supported by an incubator. Moreover, it indicates a list of advisors that provide counsel to the venture's founders. Both variables showed a relatively high correlation with the selection dummy and a relatively low correlation with the residual values.

of each word. Also, Model 5.4 shows the estimates when a Gunning Frequency of Gobbledygook (FOG)[19] is used to measure complexity, instead of the ARI index (see DuBay 2004 for further description of this index).

Models 5.5 and 5.6 present the estimates with alternative measures of the dependent variable. While the natural log of the raised capital provides a fair measure of a new venture's success, depending on the stage of fundraising, the average of raised capital can be considerably different. Even though we have controlled for the stage of fundraising in the original estimation, another way of normalizing raised capital is by dividing the natural log of the raised capital for each venture in a certain stage of fundraising (e.g. stage A) by the average value of natural log of raised capital by all the ventures in the sample in the same stage of fundraising. Model 5.5 presents the results where this alternative measure is used as the dependent variable. Due to collinearity, the control variables of stage are dropped from the covariates included in this estimation. Finally, valuation at the initial public offering (IPO) is another viable measure of success for new ventures. We obtained the IPO valuation of the new ventures in the sample (108 ventures) that reached that stage from *CrunchBase*. Since, IPO valuation happens at a single point of time, we aggregated all of the tweets made by each venture since 2010 and re-estimated LSO and LSC. The value of control variables was estimated by the state of those variables at the point of IPO. Model 5.6 presents the result of this estimation. Models 5.1-5.6 provide further evidence that the main results of the study are robust to variations in the measurement of constructs.

[19] This index is calculated by the following formula: 0.4[(# Words/# Sentences) + 100(# Complex Words/ # Words)]. In estimating the index, complex words are those with three or more syllables, excluding proper nouns and compound words.

3.8. Discussion

3.8.1. Summary of Findings

In order to gain competitive advantage, B2B firms need to situate themselves in their complex organizational landscape which entails a concurrent presence of competitor and customer firms. This means that they need to compete with competitors by differentiating themselves from them, and co-create value through collaboration with customers. Importantly, given the lesser known potential of NB2BVs to survive in such a two-sided organizational environment, any signal of the possession of the above capabilities can impact investors' sensemaking about their plausibility, and as a result, increase their success in the crucial task of fundraising. Although B2B firms can directly highlight the possession of these capabilities through their communication (e.g. emphasizing aspects of their product that differentiate them from competitors; showing their commitment to aspects of business that matter for their customer firms) in such traditional mediums as national TVs, NB2BVs can rarely benefit from such a strategy, as they often lack sufficient financial capital.

Building on the literature about signaling theory, value co-creation and differentiation, as well as the related literature about comparative linguistics (Johnson et al. 2014; Hollingshead 2011; Wickham and Walter 2007; Yoo and Alavi 2004), this paper makes the novel argument that a NB2BV's communication on social media vis-à-vis that of its competitors and customers can signal its potential for successful value co-creation and differentiation, thus impacting potential investors' funding decision.

This study of 382 Software-as-a-Service (SaaS) new ventures provides support for the signaling impact of new ventures' social media communication, demonstrating that lingual similarity (versus dissimilarity) of B2BNVs' tweets to those of customers (versus competitors) is positively associated with success in fundraising. We contend that lingual dissimilarity to competitors signals a NB2BV's potential to differentiate itself from competitors, whereas its lingual similarity to customer firms signals a greater alignment between the NB2BV and its potential customers, increasing investors' perception of the possibility of a collaborative relationship. As research shows, collaboration is crucial for B2B value creation (e.g. Dotzel and Shankar 2016) and thereby, such similarity can signal higher potential for value co-creation.

Building on the literature on strategic marketing ambidexterity, we also hypothesized that the concurrent maintenance of similarity to customers and dissimilarity to competitors signals a NB2BV's ability to be ambidextrous, a rare capability that improves firm performance (e.g., Josephson et al. 2016; Lee 2011). Consistent with this prediction, our results indicate that B2BNVs that successfully manage a concurrent similarity to their customers and dissimilarity to their competitors are more successful in raising funds than the ones that can only pursue one of these aspects.

3.8.2. Theoretical Contributions

This study offers several important theoretical contributions. First, to the best of our knowledge, this is the first attempt to understand the signaling value of social media communication and how a firm's behavior in this medium can impact business outcomes. Thus, this research contributes to the literature on the strategic impact of social media to influence perceptions of key stakeholders, such as potential investors.

Second, prior research has emphasized the need for research on how B2B firms can leverage social media (e.g., Wiersema 2013). However, the few empirical studies on the use of social media by B2B firms have been descriptive in nature (e.g., how B2B firms differ from B2C firms in their content creation; Swani et al. 2014), and have not explored the strategic payoffs B2B firms receive from utilizing social media. This study reveals an important benefit of communication on social media, by showing that lingual similarity (vs. dissimilarity) on social media to potential customers (vs. competitors) can have symbolic meanings, signaling a NB2BV's underlying qualities to potential investors, thus increasing their success in fundraising. These results are consistent with research that highlights the reliance of potential investors on indirect signals of firm qualities (e.g., Xiong and Bharadwaj 2011; Dekinder and Kohli 2008)

Third, this study sheds light on the importance of the *style* of communication (e.g., grammar, use of words) on social media. Although past research has mainly dealt with the impact of the *content* of communication (e.g., Fischer and Reuber 2014), this study takes a significant step forward by demonstrating that the structure of the communication, such as complexity and use of words, signals important information to potential investors beyond the content of the communication (see table 2, model 2.1). Specifically, we show that a multi-dimensional view of social media communication, by concurrently considering the morphological, syntactic, and semantic aspects of communication, can help understand the of the impacts of organizational communication on social media. Thus, this research contributes to a nascent stream of marketing research that explores how the linguistic pattern employed in social media communication can signal information above and beyond the content of the communication (Ludwig et al. 2013).

Fourth, this study has revealed the dynamic nature of social media communications by considering the competitive environment into consideration. Although past research on social media has mainly explored the impact of firm communication in isolation, the current work reports that the impact of a firm's communication hinges on the communication pattern of other parties in the competitive context. Thus, this study responds to a recent call in the marketing literature for understanding the impact of competitors' actions on the effectiveness of a firm's communication (Hewett et al. 2016), and is in line with research highlighting the importance of considering competitors' position (Obloj and Capron 2011). Furthermore, this study extends the existing literature by recognizing the distinct sections of the environment of a NB2BV , i.e., competitors and customers, and showing how social media communication, evaluated *relative* to these sections, can be strategically leveraged by firms.

Finally, this study contributes to the growing stream of research at the interface of marketing and entrepreneurship. Although past research has explored how such factors as the CMO characteristics can signal marketing capabilities to potential investors (Homburg et al. 2014), there is a need to understand the alternative ways in which new ventures' market-related capabilities are signaled to investors. New ventures' financial market is characterized by severe information asymmetry and search friction (Bernstein et al. 2017), due to which signals of unobservable qualities can have substantial impact on potential investors, making it important – from both theoretical and practical perspectives – to understand how such signals are sent. This study contributes to this nascent stream of research by showing that entrepreneurial B2B firms can leverage the power of social media to signal their strategic capabilities to potential investors.

3.8.3. Managerial Implications

This study also offers some practical implications. It has used a set of linguistic techniques that can be easily implemented and utilized in three distinct contexts: executives trying to develop their firms' messages on social media; executives trying to analyze competitors and customers based on their social media messages; and external investors. These implications are important, especially considering the commoditizing trends in the supply of business intelligence platforms that allow text analysis, and ubiquitous access to them at a relatively low cost.

The results of this study suggest that a NB2BV should actively manage its own communication vis-à-vis that of its competitors and potential customers. Specifically, these results encourage B2B marketers to behave strategically on social media, by suggesting that besides *what* messages are being communicated, *how* those messages are being communicated can have a substantial impact on the effectiveness of a NB2BV's social media presence. Although we don't take any stance with regard to whether firms in our sample whose tweets are highly similar to their customers and/or dissimilar to their competitors do so intentionally, and although we believe that these practices lose their impact if investors recognize that ventures are actively manipulating the lingual aspect of their tweets, still NB2BVs can benefit from the current findings. Research shows that as external entities (e.g. the stock market), try to infer the information they don't have access to from firm actions, firms might create favorable reactions by manipulating their actions (e.g. Mizik 2010). For example, Moorman et al. (2012) show that time the introduction of their innovative new products in a way that positively the stock market's valuation of them.

Second, the results of the study indicate that executives should pay careful attention to the messages conveyed by their competitors as well as customers. The style of those communications should be analyzed in addition to their content. Moreover, the sense-making activities that help understand the communication of competitors and customers should be conducted simultaneously with the development of own firm's social media strategies.

Finally, the study provides insights for investors in entrepreneurial firms, by showing the effects of LSO and LSC on the eventual valuation at IPO, and thus suggesting that they are reliable indicators of the sustained success of new ventures. The results suggest that investors can evaluate the distinctiveness of a venture to its competitors, as well as its potential alignment with customers by monitoring its communication on social media platforms such as *Twitter*.

3.8.4. Limitations and Directions for Future Research

This study offers several avenues for further research. First, the current research offers preliminary insight regarding the impact that a NB2BV's communication on social media can have on its business outcomes. We argue that this is due to social media's role in signaling a firm's capabilities. However, the nature of the data does not allow directly examining the underlying signaling process. Future research could use other research methods (e.g., survey, qualitative studies), to directly explore this underlying mechanism.

Second, although our specification controls for several established variables that can impact investors' decisions, there could be other important variables for which we have not controlled. The results remain robust to removing time-invariant unobserved heterogeneity, as evidenced by the results of the random- (GLS) and fixed-effects estimations, but future research can further enhance their generalizability by controlling for time-variant factors.

Third, this study has focused on NB2BVs. Further research is needed to examine whether the observed consequences of signaling via social media apply to other contexts, including B2C new ventures.

Finally, the focus of this investigation has been limited to firms' communication on *Twitter*. Future research can expand the scope of the research, by investigating firms' communication in other outlets (e.g., firms' website, other social media platforms, etc.).

Tables of Chapter 3

Table 1: Correlation Matrix[a]

	Mean	S.D.	1	2	3	4	5	6
1. Topic Similarity to customer industry	4.93	0.21						
2. Sentiment similarity to customer industry	0.82	0.18	0.77***					
3. Complexity similarity to customer industry	7.23	3.06	0.69***	0.58***				
4. Topic Similarity to own industry	4.84	0.39	0.01	0.01	-0.01			
5. Sentiment similarity to own industry	0.78	0.23	-0.01	0.02	0.03	0.71***		
6. Complexity similarity to own industry	6.84	2.73	0.01	0.01	0.03	0.78***	0.63***	
7. Natural log of raised capital	14.24	14.39	0.12***	0.12***	0.28***	-0.31***	-0.11***	-0.23***

[a] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $N = 1{,}224$.

Table 2: Main Analysis[a,b]

	DV = Raised Capital	GLS Model 2.1	GLS Model 2.2	GLS Model 2.3	AB-GMM Model 2.4	Fixed Effect Model 2.5
Lingual similarity to customer (LSC)	Topic similarity to customer industry	0.175*** (0.037)	0.079* (0.036)	0.073* (0.036)	0.064* (0.025)	0.077* (0.032)
	Sentiment similarity to customer industry	0.037* (0.018)				
	Complexity similarity to customer industry	0.065* (0.027)				
Lingual similarity to own (LSO)	Topic similarity to own industry	-0.189*** (0.048)	-0.085** (0.027)	-0.023* (0.010)	-0.011* (0.005)	-0.076* (0.033)
	Sentiment similarity to own industry	-0.045* (0.022)				
	Complexity similarity to own industry	-0.081** (0.025)				
Interaction Term	LSO*LSC			-0.085** (0.032)	-0.084* (0.043)	-0.063* (0.027)
Controls	Sentiment of tweets	0.076 (0.052)	0.069* (0.033)	0.028 (0.019)	0.028 (0.018)	0.03 (0.02)
	Richness of vocabulary	0.102* (0.047)	0.019 (0.01)	0.025 (0.015)	0.057 (0.046)	0.072 (0.05)
	Complexity of tweets	0.058 (0.044)	0.025 (0.016)	0.019 (0.015)	0.038 (0.025)	0.048 (0.028)
	# of Employees	0.011* (0.005)	0.018* (0.009)	0.029* (0.013)	0.033* (0.015)	0.017* (0.008)
	Education of employees	0.077*** (0.009)	0.074** (0.025)	0.082*** (0.015)	0.083 (0.072)	0.095*** (0.013)
	Years since establishment	0.022** (0.008)	0.016** (0.005)	0.012* (0.005)	0.061** (0.021)	0.023* (0.009)
	Wald's χ^2	3,339.2	3,128.2	3,715.8	4,102.5	4,819.4
	N	1,224	1,224	1,224	1,224	1,224

[a] ** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard error of coefficients of estimates are presented in parenthesis. GLS estimation with corrections for panel-specific AR1 and heteroscedasticity is used.*

[b] *All Wald's χ^2 estimates are significant at $p < 0.001$ level. The coefficients of dummy variables (for own industry, customer industry, location, year, and stage) are excluded for brevity.*

Table 3. Garen's Correction[a,b]

DV =	LSO (Stage1A) Model 3.1	LSC (Stage1B) Model 3.2	Raised Capital (Stage 2) Model 3.3
Lingual similarity to customer industry (LSC)			0.019* (0.009)
Lingual similarity to own industry (LSO)			-0.026** (0.01)
LSO*LSC			-0.066** (0.023)
Sentiment of tweets			0.022 (0.018)
Richness of vocabulary			0.096 (0.084)
Complexity of tweets			0.041* (0.016)
# of Employees	0.004 (0.003)	0.006(0.005)	0.023* (0.009)
Education of employees	0.009 (0.005)	-0.003(0.003)	0.026* (0.012)
Years since establishment	-0.004 (0.003)	-0.008(0.006)	0.056** (0.02)
Geographical Proximity to Own Industry (GPO)	0.073** (0.024)		-0.003 (0.002)
Geographical proximity to customer industry (GPC)		0.091* (0.045)	0.005 (0.003)
Founders' knowledge of own industry (FKO)	0.086*** (0.016)		0.008 (0.005)
Founders' knowledge of customer industry (FKC)		0.103** (0.033)	0.010 (0.006)
ŋ(Stage1A)			-0.062** (0.023)
ŋ(Stage1A)*LSO			0.009 (0.007)
ŋ(Stage1B)			0.033** (0.011)
ŋ(Stage1B)*LSO			0.011 (0.008)
Wald's χ^2	873.6	667.9	4,558.20
N	1,224	1,224	1,224

[a] *# $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard error of coefficients of estimates are presented in parenthesis. GLS estimation with corrections for panel-specific AR1 and Heteroscedasticity is used.*

[b] *All Wald's χ^2 estimates are significant at $p < 0.001$ level. The coefficients of dummy variables (for own industry, customer industry, location, year, and stage) are excluded for brevity.*

Table 4: Heckman's Procedure Results[a,b]

DV =	Selection Model 4.1	Raised Capital Model 4.2
Lingual similarity to customer industry (LSC)		0.068** (0.026)
Lingual similarity to own industry (LSO)		-0.019* (0.009)
LSO*LSC		-0.057** (0.020)
Sentiment of tweets	0.031* (0.016)	0.053* (0.025)
Richness of vocabulary	0.012 (0.007)	0.009 (0.008)
Complexity of tweets	0.023 (0.017)	0.031* (0.013)
# of Employees	0.008 (0.004)	0.012 (0.009)
Education of employees	0.019 (0.017)	0.102*** (0.023)
Years since establishment	0.153*** (0.016)	0.010* (0.005)
Incubator?	0.088** (0.032)	
Advisor?	0.094*** (0.01)	
Wald's χ^2	2,583.6	

[a] *# p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001; Standard error of coefficients of estimates are presented in parenthesis. GLS estimation with corrections for panel-specific AR1 and Heteroscedasticity is used. N= 1,224.*

[b] *All Wald's χ^2 estimates are significant at p < 0.001 level. The coefficients of dummy variables (for own industry, customer industry, location, year, and stage) are excluded for brevity.*

Table 5: Alternative Measurements of Independent and Dependent Variables[a,b]

	TriGrams Model 5.1[c]	#Hashtags Model 5.2	ANEW Model 5.3	FOG Model 5.4	Normalized Raised Capital Model 5.5	IPO Valuation Model 5.6
Lingual similarity to customer industry	0.026*	0.091***	0.034**	0.018*	0.087***	0.091***
(LSC)	(0.012)	(0.018)	(0.011)	(0.007)	(0.018)	(0.026)
Lingual similarity to own industry	-0.027*	-0.067**	-0.026*	-0.011*	-0.037**	-0.102*
(LSO)	(0.011)	(0.023)	(0.01)	(0.005)	(0.012)	(0.046)
LSO*LSC	-0.056*	0.105***	-0.053***	-0.104***	-0.067**	-0.078***
	(0.029)	(0.015)	(0.01)	(0.017)	(0.024)	(0.012)
Sentiment of tweets	0.031	0.028*	0.034	0.032	0.029	0.064
	(0.025)	(0.012)	(0.025)	(0.018)	(0.022)	(0.054)
Richness of vocabulary	0.032	0.014	0.025	0.061*	0.073	0.088**
	(0.02)	(0.008)	(0.022)	(0.03)	(0.04)	(0.034)
Complexity of tweets	0.058	0.061*	0.042*	0.034*	0.041	0.024
	(0.031)	(0.024)	(0.021)	(0.014)	(0.034)	(0.018)
# Employees	0.011*	0.094**	0.017*	0.023*	0.017*	0.018
	(0.005)	(0.032)	(0.007)	(0.011)	(0.008)	(0.014)
Education of employees	0.099**	0.114***	0.104***	0.079*	0.086*	0.056**
	(0.036)	(0.013)	(0.014)	(0.032)	(0.042)	(0.02)
Years since establishment	0.013*	0.008	0.012	0.045*	0.027**	0.017*
	(0.006)	(0.007)	(0.009)	(0.02)	(0.009)	(0.007)
Wald's χ^2	4,121.5	6,117.8	4,451.2	3,478.4	4,182.3	1,892.3
N	1,224	1,224	1,224	1,224	1,224	108

[a] ** p < 0.05, ** p < 0.01, *** p< 0.001; Standard error of coefficients of estimates are presented in parenthesis. GLS estimation with corrections for panel-specific AR1 and Heteroscedasticity is used.*

[b] *All Wald's* $\boldsymbol{\chi}^2$*estimates are significant at p < 0.001 level. The coefficients of dummy variables (for own industry, customer industry, location, year, and stage) are excluded for brevity.*

[c] *Models 5.1-5.4 present the estimation results of models with alternative measures of topic similarity (5.1 and 5.2), sentiment similarity (5.3), and complexity similarity (5.4). Models 5.5 and 5.6 present the results of estimation with alternative dependent variables.*

Figures of Chapter 3

	Lingual Aspect	Lingual Analysis Based on Johnson et al. 2014	Operationalization Based on Johnson et al. 2014
Content of Communication	Topic Similarity	Syntactic Analysis	Bi-gram Entropy
	Sentiment Similarity	Semantic Analysis	Positivity Valence
Style of Communication	Complexity Similarity	Morphological Analysis	Readability Index

Figure 1: Lingual aspects explored in the current study

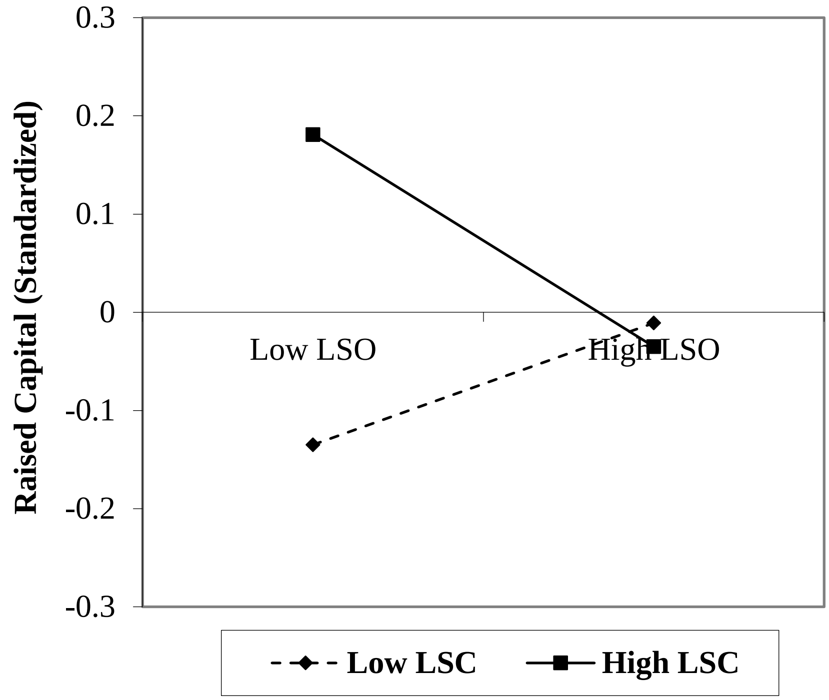

Figure 2: Interaction Plot Between Lingual Similarity to Own Industry (LSO) and Lingual Similarity to Customers (LSC)

Appendix: Summary of Variable Operationalization and Data Sources

Variable	**Operationalization**	**Source**	**Type of analyses***
Raised capital	Total dollar value of capital raised in each round	*Angel.Co*	Main
IPO valuation	The dollar value of the venture at IPO	*CrunchBase*	Alternative
Topic similarity	Inverse of mean of the sentence entropy (based on bi-grams) across all sentences comprising the tweets of a focal venture		Main
	Inverse of mean of the sentence entropy (based on tri-grams) across all sentences comprising the tweets of a focal venture		Alternative
Sentiment similarity	Inverse of absolute difference between the polarity index (using AFINN dictionary) of the new venture and the mean polarity index of its competitors (or customers)		Main
	Inverse of absolute difference between the polarity index (using ANEW dictionary) of the new venture and the mean polarity index of its competitors (or customers)	*Twitter*	Alternative
Complexity similarity	Inverse of absolute difference between the ARI of the new venture and the mean ARI of its competitors (or customers)		Main
	Inverse of absolute difference between the FOG index of the new venture and the mean of FOG indices of its competitors (or customers)		Alternative
Stage indices	Number of capital raising rounds (for each index) per stage (e.g. seeding, Stage A, Stage B, etc.)		
Size	Number of employees	*Angel.Co*	
Location	City at which the B2BNV is based at		
Education	Employees' average level of education	*LinkedIn*	
Customer industry	Two-digit SIC code matched with customer tags from *Angel.Co*	*Angel.Co* and *COMPUSTAT*	Main
Own industry	Self-specified tags		
Sentiment	Weighted positivity of B2BNV tweets (using AFINN dictionary)		
Richness of Vocabulary	Number of unique words used in B2BNV tweets	*Twitter*	
Complexity	Average ARI of B2BNV tweets		

**Main variables are used in the main analysis. Alternative variables are used in add*

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