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Big Data and Organizational Impacts: A Study of Big Data Ventures

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Big Data and Organizational Impacts: A Study of Big Data Ventures

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Abstract

New information technology (IT) ventures are at the forefront of developing IT innovations. In spite of their importance in the advancement of IT and the unique risks of survival that distinguishes them from established firms, the organizational literature on IT has mostly overlooked new IT ventures. Specifically, Big Data industry is a context where new IT ventures actively change the landscape of IT innovations. However, less is known about the factors influencing the economic success of Big Data ventures (BDVs), as well as the established firms that invest in them. To shed light on these factors, three essays are designed and executed.

The first essay investigates the value proposition of a BDV's product/service as an important constituent of its business model and seeks to understand how it affects the capital raised by BDVs in their early stages of development. Then, the second essay is concerned with the role that the network embeddedness of a BDV plays in its success. Building on the notion of socially-constructed innovations, this essay examines the suitable network structures that help BDVs succeed. Finally, the third essay focuses on a BDV's strategy in management of its communication with the potential investors on social media platforms. In this essay, we extend the previous literature that had highlighted the importance of the verbal content of communication on social media platforms for a new venture's success and in turn focus on the non-verbal aspects of communication in social media. Building on the notion of symbolic actions to theorize about non-verbal communication, we focus on the sequence of message narrators in social media and investigate the different tactics BDVs follow to raise capital.

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Chapter 1: Introduction

New IT ventures are at the forefront of developing information technology (IT) innovations, some of which have transformed the way the modern society, as well as the modern economy, function. For example, in the growing economy of Big Data, our preliminary examination of the Big Data initiatives[1], pursued by established firms, shows a significant presence of investments in new Big Data ventures (BDVs). *uBiome*is one of these BDVs that has developed a platform that utilizes the Big Data science to investigate human microbiomes and present the outcome of its discoveries to healthcare and pharmaceutical companies. *uBiome* is among the first industry-scale initiatives to understand human microbiomes through analyzing masses of data coming from thousands of patients around the globe. It revolutionizes the way that the interrelations among diseases, as well as the effectiveness of drugs, are understood.

New ventures face higher risks of survival compared to the bigger and more established firms (MacMillan and Day 1987). Most notably, they face threats of newness and smallness (e.g., Leung et al. 2006). Because of their unknown nature, or lack of a clear business history, their access to financial capital is challenging (threat of newness). Also, because of their organic organization (Covin and Slevin 1990) and extremely small size (Lu and Beamish 2006), they often face a fierce competition from the competitors that usually benefit from economies of scale (MacMillan and Day 1987).

In spite of their importance in advancement of ITand the unique risks of survival that distinguishes them from established firms, the organizational literature on IT has overlooked new IT ventures for the most part.We searched the *Web of Science* database to see if the keywords "new venture" or "startup" have been mentioned in *AIS*' basket-of-eight journals; the search in

[1]Out of 842 Big Data investments by businesses from 2009 to 2014 found in press news (collected from Lexis/Nexis), 615 (73%) were investments in BDVs.

Web of Science returns only seven results (Janson et al. 1997; Leidner 1999; Siau 1999; Poon 2000; Winter and Gill 2001; Custodio et al. 2006; Laffey 2007), none of which appearin the top-three journals of the field (*MIS Quarterly, Information Systems Research, and Journal of Management Information Systems*). While one of the seven studies discusses the usefulness of e-commerce togeneral startups (Poon 2000), the other six studies are examinations of new IT venture single cases, which have mostly focused on the new technology introduced by the venture, rather than investigating the venture's roadmap to success. Therefore, this dissertation intends to investigate factors that affect the economic success of new IT ventures, and BDVs specifically, as less understood organizational forms.

At an abstract level, we treat the question about the economic success of new IT ventures as the overarching theoretical phenomenon of interest. We study this phenomenon in the Big Data context as an important emerging area in which new IT ventures have a salient presence. Specifically, we design and execute three essays that shed light on factors influencing the economic success ofBDVs, as well as the established firms that invest in them. In the design of the three essays, we expand our attention to the strategic aspects of success of new IT ventures and the context-specific insights pertaining to BDVs. Below we briefly introduce each essay.

A Three-Essay Research Approach

The first essay (Chapter 2) investigates the value proposition of a BDV's product/service as an important constituent of its business model and seeks to understand how it affects the capital raised by BDVs in their early stages of development. In this study, we identify different technological scopes prevalent in the Big Data context and discuss the value propositions that best fit each scope. Moreover, we examine the value that BDVs generate for their well-established investors. In doing so, we consider the environmental characteristics of the investing firm as a factor that moderates the effect of a BDV's value proposition.

We assess a BDV's value proposition by investigating its verbal communication with the potential investors, reflected in its product/service description statements. Moreover, we complement our examination of a BDV's verbal communication by surveying the value propositions communicated to the potential investors indirectly, mostly through third-party blog posts, or news pieces about the BDV. This study uses a mixture of qualitative and quantitative approaches and utilizes data crawled from a focal BDV's web pagesand archival data.Specifically, a text-analytics approach is followed to make sense of value propositions offered by a BDV, and an event study approach is used in examining the economic payoff of investing in BDVs by established firms.

The second essay (Chapter 3) is concerned with the role that the network embeddedness of a BDV plays in its success. The existing research on entrepreneurial success has emphasized the effect of network embeddedness, especially in providing access to the investors. Nonetheless, the role of embeddedness in development and refinement of innovation and its effect on a new venture's success is understudied. Networks play a pertinent role in the development of a new venture's innovation, especially if the product/service is developed in an industry where innovation is socially-constructed. While regulation, patenting trends, and other social norms may make developing an innovation possible within the boundaries of individual firms, we argue that IT innovations, specifically in the area of Big Data, can be constructed socially. Building on the notion of socially-constructed innovations, this essay examines the suitable network structures that help BDVs succeed. Specifically, those networks supplying intellectual capital to a BDV are studied along with those supplying access to financial capital.

Further, this essay conducts a comparison between the IT context, i.e., Big Data, and a non-IT context, i.e., Medical Devices. The purpose of this comparison is to understand the potential unique outcomes of network embeddedness for new IT ventures compared to their peers in other industries.

A secondary focus in this essay is to simultaneously investigate the different types of networks that new ventures are embedded inand investigate whether separating or aggregating the ties from the different networks can better explain the economic benefits that the ventures receive.

This quantitative study combines data gathered from the first study with the founders' and investors' networks of affiliation to investigate the proposed research models. In conducting this essay, networks of co-founders, employees, and investors are mapped and then transformed to examine the inter-venture networks that supply a BDV with intellectual or financial capital. In studying the network effects, the network structures are measured longitudinally, across each round of fundraising for each BDV, and a panel of BDVs across rounds of fundraising are examined. Further, a matched-sample methodology is used to conduct the comparison between the models run in the Big Data and Medical Devices Industry, to ensure a fair comparison.

The third essay (Chapter 4) focuses on a BDV's strategy in management of its communication with the potential investors on social media platforms. In this essay, we intend to extend the previous literature that had highlighted the importance of the verbal content of communication on social media platforms for a new venture's successand in turn focus on non-verbal aspects of communication in social media. Building on the notion of symbolic actions to theorize about non-verbal communication, we focus on the sequence of message narrators in social media and investigate the different tactics BDVs follow to raise capital.

A second focus of this essay is on examining the extent to which non-verbal communication tactics in one platform instigate reaction (in form of Word-of-mouth, WoM) in another platform. Specifically, we discuss that the BDVs face an environment in which fundraising activities are not limited to the macro-investors(e.g., angels and venture capitalists) and extend to micro-investors in form of crowdfunding. Accordingly, social media activities extend beyond attracting audiences in platforms which are designed for macro-investors and include communication with micro-investors in more publicly accessible platforms. Since a new venture's activities in one platform are visible to the audience in another, investigating cross-platform effects can inform entrepreneurs about ways in which they can coordinate their social media efforts.

The third essay follows an inductive approach, where we utilize event-sequence analysis to identify beneficial non-verbal communication tactics followed by BDVs in macro- and micro-investor platforms. We then assess the effect that these tactics have on the raised capital and examine the possible cross-platform effects in a longitudinal study. Similar to Essay 2, this essay's quantitative analysis is conducted on a panel of BDVs followed in multiple rounds of fundraising. Table 1 summarizes these three essays, in terms of their research question(s), theoretical focus, and methodology.

References

Covin, J. G., and D. P. Slevin. 1990, "New Venture Strategic Posture, Structure, and Performance: An Industry Life Cycle Analysis," *Journal of Business Venturing* (5:2), pp. 123-135.

Custodio, M., A. Thorogood, and P. Yetton. 2006, "24 X 7 @ Full Speed: Accelerated Time to Market," *Journal of Information Technology* (21:2), JUN, pp. 116-126.

Janson, M., A. Brown, and T. Taillieu. 1997, "Colruyt: An Organization Committed to Communication," *Information Systems Journal* (7:3), JUL, pp. 175-199.

Laffey, D. 2007, "The Ultimate Bluff: A Case Study of Partygaming.Com," *Journal of Information Technology* (22:4), DEC, pp. 479-488.

Leidner, D. 1999, "Virtual Partnerships in Support of Electronic Commerce: The Case of TCIS," *Journal of Strategic Information Systems* (8:1), MAR, pp. 105-117.

Leung, A., J. Zhang, P. K. Wong, and M. Der Foo. 2006, "The use of Networks in Human Resource Acquisition for Entrepreneurial Firms: Multiple "fit" Considerations," *Journal of Business Venturing* (21:5), pp. 664-686.

Lu, J. W., and P. W. Beamish. 2006, "Partnering Strategies and Performance of SMEs' International Joint Ventures," *Journal of Business Venturing* (21:4), pp. 461-486.

MacMillan, I. C., and D. L. Day. 1987, "Corporate Ventures into Industrial Markets: Dynamics of Aggressive Entry," *Journal of Business Venturing* (2:1), pp. 29-39.

Poon, S. 2000, "Business Environment and Internet Commerce Benefit - a Small Business Perspective," *European Journal of Information Systems* (9:2), JUN, pp. 72-81.

Siau, K. 1999, "Xcert Software, Inc." *Journal of Information Technology* (14:3), SEP, pp. 235-242.

Winter, S., and T. Gill. 2001, "OFFICETECH (R): A New Paradigm in Office Services?" *Journal of Information Technology* (16:1), MAR, pp. 23-32.

Table 1. Overview of the Dissertation Essays

	Essay 1	Essay 2	Essay 3
Research Question(s)	1. How do a BDV's value propositions affect its success? 2. How do the environmental characteristics of an investing firm interact with the BDV's value propositions to affect the success for investing firms?	1. How does the embeddedness of a BDV in intellectual and financial capital networks affect its success? 2. Are there any differences between the social construction of IT innovations and innovations developed in other industries?	1. What are the prevalent non-verbal communication strategies that BDVs pursue? 2. Are there any cross-platform effects for non-verbal communication strategies followed in macro- and micro-investor social media platforms?
Theoretical Focus	Business Models	Social Networks	Non-Verbal Symbolic Communication
Methodology	Qualitative (content analysis)/ Quantitative (event study)	Qualitative (content analysis)/ Quantitative (longitudinal panel, social networks analysis)	Qualitative (content analysis)/ Quantitative (longitudinal panel, event sequence analysis)
Data	• Crawled data from webpages • Archival	• Crawled data from webpages	• Crawled data from webpages

Chapter2:
Big Data and Organizational Impacts: A Study of Investment in Big Data Ventures

Abstract

Due to their versatility, Big Data ventures (BDVs) have become a prevalent choice of investment for conventional firms that perceive the risk of investment in Big Data technologies to be high. However, less is known about how BDVs produce rent for their investing partners. Utilizing a business model lens, this study proposes that the value emphasis and technological scope of a BDV's business model interact to influence the market performance of the investing firms. Further, we hypothesize that the environmental uncertainty of the investing firm is another interacting factor, influencing the effect that the value emphasis has on the performance of investing firms. Adopting an event-study approach, we test our hypotheses by forming a sample of 651 public announcements about firms that have invested in BDVs from 2010 to 2013 and found that a BDV's emphasizing tackling Big Data challenges (i.e., volume, velocity, variety, and veracity) increases abnormal returns for the investing firm, although such benefits are contingent on the technological scope of the BDV's innovation (i.e., Big Data security, analytics, or Big Data infrastructure) and the investing firm's environmental dynamism, complexity, and munificence.

Key words: *Big Data venture, Big Data investment, business model, value emphasis, technological scope, environmental uncertainty, event-study.*

Introduction

In the "Big Data" era, where the volume, velocity, and veracity of data available to organizations exceeds the capacity of traditional data processing applications (Chen et al. 2012), organizations strive to use new generations of technology to process fast-flowing information and produce competitive intelligence. According to one report, 64 percent of US firms had already invested or planned to invest in "Big Data technologies" in 2013 (Gartner 2014). Big Data technologies are directed at finding ways to effectively assimilate voluminous and fast-flowing data into the day-to-day conduct of firms (Gartner 2014) and range from infrastructural investments in new data processing platforms to advanced business intelligence and analytics applications. In the Big Data era, groundbreaking technological advancements have changed the nature of information technology (IT) investments, making their costs higher than what most medium-sized firms can afford (Jacobs 2009). Moreover, risks associated with Big Data investments are considered to be higher than with conventional IT investments (Chen et al. 2012). The high cost of Big Data investments (BDIs), coupled with their high risk, has resulted in a growing mode of IT investment that is no longer internally driven.

In turn, start-ups pursuing Big Data ventures (BDVs) represent a prevalent organizational form due to their versatility and risk-taking nature in design and development of Big Data technologies. BDVs are considered to be an important way of involving larger firms in Big Data Initiatives (BDIs). In fact, larger firms try to pursue BDIs through the proxy of BDVs, by investing in their venture capital, or acquiring them. Gobble (2013, p. 65) describes the emergence of BDVs:

> "…A number of promising start-ups are offering new ways to collect, store and analyze data; in 2011 and 2012 Wall Street Journal profiled several of these companies in a series of blog posts."

Similarly, results of our preliminary study of publicly-announced BDIs in 2013 show that 73 percent of organizations' BDIs can be categorized as external investment in Big Data ventures (BDVs).

Unlike conventional IT investments, investment in BDVs adds value through external partnership with another firm, i.e., the start-up company owning the venture. Literature on the value of IT in organizations has mainly focused on how IT as an internal production factor (e.g., Brynjolfsson and Hitt 2000), resource (e.g., Wade and Hulland 2004), or capability (e.g., Pavlou and El Sawy 2006) enables organizations to compete with rivals and produce economic gain. However, this literature informs us less about value addition through investments in IT ventures, generally, and BDVs, specifically. Because of their external focus, value-adding mechanisms in ventures are different from those mechanisms in conventional organizations (Zott and Amit 2007) and thusrequire more research to unfold.

Moreover, Big Data technologies change the data focus of organizations from within-enterprise data (i.e., own suppliers, own firm, own customers) to outside-of-the-enterprise data (i.e., potential suppliers, potential customers) (Chen et al. 2012). Due to their role in triggering major changes in the architecture of data in firms, Big Data investments have become an important area of interest within information systems (IS), with academia responding through redefined research agendas (Kumar et al. 2013; Goes 2014). Recent IS literature has focused on BDIs as the means to gain competitive advantage (Agarwal and Dhar 2014) and called for research that transcends the professional speculations around BDIs (Chen et al. 2012) by investigating their value-creation mechanisms (Agarwal and Dhar 2014) and impacts on organizational practices (Goes 2014) and organizational strategies (Bharadwaj et al. 2013).

In spite of the prevalence and importance of Big Data for contemporary firms, and although there have been calls for research on the economic payoffs of investment in Big Data (e.g., Goes 2014), this research is in infancy stages, and other than few exceptions (e.g., Tambe 2014), there has not been much research on the topic. Specifically, and to the best of our knowledge, there has been no empirical study that investigates investment in BDVsas a prevalent mode of investment in Big Data. In summary, investment in BDVs presents two fresh challenges to the field of information systems (IS): (a) it presents an external mode of investment in IT that differs from the traditional in-house investments studied in the previous literature; and (b) it involves investment in a type of technology that is distinctively different from the conventional IT and can change the way that value is created by IT. To overcome these challenges, we intend to address the following research question: *"What strategic and environmental factors influence the value of investments in BDVs?"*

We adopt the lens of business models (BMs) to understand value-adding mechanisms of BDVs for firms that invest in them. A BM "elucidates how an organization is linked to external stakeholders, and how it engages in economic exchanges with them to create value for all exchange partners" (Amit and Zott 2001, p. 511). Recent IS studies have called for better understanding of the value creation of IT through the lens of BM (e.g., Rai and Tang 2013, Bharadwaj et al. 2013). Specifically, we view a BDV's BM as the way by which it presents its innovation to the marketand draws a path to success for its investors. Since many BDVs are in the initial phases of innovation inception, their BM can be the most tangible interface that can predict their profitability for investing firms.[2]

[2]Because of the novel nature of Big Data technologies most active BDVs are at the product development stages and are still away from the organizational maturity at the initial public

Further and building on the resource-based view (RBV) in the IT context, we suggest that the BDV's and the investing firm's industry influence the effect that a BDV's BM has on performance of the investing firm. In hypothesizing about the role of the BDV's BM, as well as the BDV's and the investing firm's environment, we suggest that a BDV's BM involves value emphases on the ways in which the BDV's innovation helps an investing firm overcome any of the Big Data challenges of volume, velocity, variety, or veracity of data. Then, we conceptualize a BDV's environment as the technological scope (i.e., Big Data infrastructure, Big Data security, Big Data analytics) at which the BDV's innovation operates. Finally, and following the previous research (Miller and Friesen 1980; Newkirk and Lederer, 2006; Yayla and Hu 2012), we conceptualize the investing firm's environment through three dimensions of dynamism, complexity, and munificence. We hypothesize and test that the Big Data emphasis, the scope of a BDV, and the investing firm's environmental uncertainty interact to generate value for the investing firm. Despite being guided by the literature on business models in entrepreneurial firms and RBV to identify potential factors explaining the value of BDVs for established firms, the study takes an explorative approach in unfolding the way in which the identified factors affect the value of BDVs. Specifically, this approach is plausible given the rather understudied nature of the Big Data industry, as well as the economic ways in which IT start-ups create value for their investors.

Given the pronounced importance of Big Data investments for firms (e.g., Agarwal and Dhar 2014), we expect that an event study approach enables us to assess the profitability of investments in BDVs by measuring the impact that public announcements about investments in BDVs have on the investing firms' market value. Using a longitudinal study of 651 public

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offering (IPO) stage. As a result, in absence of mature organizational structures, their business model is one of the few signals they can send to the market about their success potentials.

announcements of investment in BDVs from 2010-2013, we find that the value of different emphases on Big Data challenges is contingent onthe technological scope of the BDV's innovation and the investing firm's environment. Further, our results shed light on the emerging trends in Big Data markets and offeractionable implications for the managers of investing firms, as well as for Big Data entrepreneurs.

Theoretical Development

Business Models

Business models of IS firms are viewed as mediums that explain how a technological innovation results in business success (e.g., Al-Debei and Avison 2010). They provide a narrative that explains how a technological product/service can gain traction in a marketand achieve and maintain its competitive position (Pateli and Giaglis 2004). In spite of their appeal to the organizational studies focusing on the success of IS-centric firms (Eriksson and Penker 2000, Pouloudi et al. 2003, Vassilopoulou et al. 2003, Hedman and Kalling 2003, Klueber 2000), limited consensus exists on the definition of business models. For example, Al-Debei and Avison (2010) note that:

> "To date, the BM concept is still considered an ill-defined buzzword. It is suggested that the BM concept is 'murky' at best. Some other researchers argue that the concept is underdeveloped. In addition, the BM concept has sometimes been misperceived as a substitute of corporate strategy, business process, or business case."

The existing literature on business models has attempted to clarify the definition of business models by identifying its components (e.g., Dubosson-Torbay et al. 2002, Pateli and Giaglis 2004, Al-Debei and Avison 2010). Among the most agreed-upon components, especially in the early stages of development in entrepreneurial firms (Dubosson-Torbay et al. 2002), is value emphasis (Amit and Zott 2001, Petrovic et al. 2001, Magretta 2002, Osterwalder et al. 2005). Value emphasis explains the source of a product's/service's value creation for its customers/users (Amit and Zott 2001). The extant empirical research on business models has often surveyed business models by describing value emphasis (e.g., Bonaccorsi et al. 2006; Susarla et al. 2009; Brynjolfsson et al. 2010; Demirkan et al. 2010; Casadesus-Masanell and Llanes 2011; Casadesus-Masanell and Llanes 2011; Deodahr et al. 2012; VandeMeer et al. 2012; Lin et al. 2012; Liu et al. 2014; Niculescu and Wu 2014).

Business Models and Performance

Performance of new ventures critically depends on their boundary-spanning arrangements (Hite and Hesterly 2001). Among these boundary-spanning arrangements are their business models where they promote themselves as attractive investments for potential investors. In fact, a business model is considered an important pillar of new ventures because they need a convincing logic and narrative in order to attract investorsand expand. Especially in early stages of their existence, when the venture's service/product is not presented to customers at a large scale (Hand 2007), a business model operates as one of the main measures for the market to evaluate overall benefits of investment in the venture (Zott and Amit 2007). Since business models explain how value is created for an external partner (e.g., an investing firm), assessing them can explain payoffs for investing firms.

The existing literature on the effect of business models on firm performance suggests that business models can be a source of competitive advantage (Markides and Charitou 2004; Casadesus-Masanell and Ricart, 2010). Particularly, Zott et al. (2011, p.1029) note that more novel and effective models can result in superior value-creation for stakeholders:

> "The novelty presented by new, effective models can result in superior value creation"

As a result, by investing in BDVs with superior business models (that are new and effective), a firm can gain competitive advantage over its rivals.

A BDV's Business Model and Investing Firm's Market Performance

Building on the general literature on business models and firm performance, we develop a logic that explains how the value of investments in BDVs can be inferred by assessing the BDV's business model. Business models present a narrative through broadcasting the value emphasis of a venture. Value emphasis signals the way in which value is to be created for stakeholders. However, the same value emphasis in one technological scope might not be as novel in another. The technological scope of business models defines the context in which value is created. In fact, the technological scope operates as an environment where the value emphasis of a BM should be interpreted. Thus, in order to assess the value of BDV for an investing firm, its value emphasis should be examined in the technological scope in which it is presented. If in a given technological scope, the value emphasis of a BDV is novel and effective, then competitive advantage, and thereby increased market returns, can be expected for the investing firm.

In addition to the technological scope, the environmental uncertainty of the investing firm can also influence the effect of the focal BDV's value emphasis. Specifically, the resource-based view in IT suggests that organizational uncertainty is a contingency factor that influences the plausibility and attractiveness of resources and investments for organizations (Wade and Hulland 2004). Wade and Hulland (2004) contend (p. 126) that:

> "The relationship between IS resources and firm performance is affected not only by internal elements …, but also by environmental factors. These factors reflect the uncertainty in an organization's operating environment. Drawing on the work of Aldrich (1979), Child (1972), and Pfeffer and Salancik (1978), Dess and Beard (1984) concluded that three dimensions of the environment contribute most to environmental uncertainty and are thus most likely to consistently influence firm performance over time: environmental dynamism, munificence, and complexity."

Thus, the performance payoffs of investment in BDVs, as an emerging mode of investment in IS resources, can be affected by the three dimensions of environmental uncertainty, namely, dynamism, complexity, and munificence. Overall, we suggest that the effect of a BDV's value emphasis on the payoffs for the investing firm depends on the environment of the BDV, i.e., its technological scope, and the environment of the investing firm. In the below section, we discuss the value emphasis in BDVs, explain the prevalent technological scope in BD, and discuss the relevance of environmental uncertainty to BD investments.

A BDV's Value Emphasis

The existing literature offers a variety of lenses to think of the value emphasis dimension of a business model in a BDV. For example, Amit and Zott (2001) suggest a typology that is consisted of four value emphases, i.e., innovativeness, efficiency, complementarity, and lock-in. Similarly, Zott and Amit (2007) focus on a combined pursuit of both efficiency and innovativeness as another value emphasis. Nonetheless, the existing frameworks to model value emphases of business models are too broad to fit the distinct nature of Big Data technologies and innovations. In this study, we build on the existing literature on Big Data technologies and frame value emphases of Big Data innovations around the specific purpose they are designed for.

There is almost a unanimous agreement that Big Data technologies create *value*, through harnessing the volume, velocity, variety, veracity of data (Lee et al. 2014). The challenge of data *volume* refers to the vast amount of data that is generated and is accessible for making sense of (Chen et al. 2012). Not only is the massive size of data available to firms in Big Data era challenging, the speed at which it flows also represents a threat. This is what the challenge of *velocity* refers to (Jagadish et al. 2014). While these two challenges are the most discussed in the Big Data literature (Lee et al. 2014), other challenges are also present. Specifically, data available to contemporary firms can come in various formats (e.g., text, video, hypertext) and from different sources (e.g., social media, competitors' webpages, etc.). This refers to the challenge of data *variety* (Jagadish et al. 2014). Finally, data *veracity*, i.e., susceptibility of data to correctness and accuracy (Normandeau 2013) is another challenge that Big Data technologies must respond to. Building on these agreed-upon challenges and expectations from Big Data technologies to overcome them, we suggest that a Big Data innovation by a BDV can propose to create value for its investors by emphasizing any of the four areas of Big Data challenge. Therefore, emphasizing the ability to tackle each of the 4Vs challenges signals a BDV's proposed way of creating value for its stakeholders, and hence, its investors[3].

We define the *volume emphasis* of a BDV's innovation as the focus of the product on collecting, updating, screening, maintaining, or analyzing large data sets. Further, we define the *velocity emphasis* of a BDV's innovation as the focus of the product on timely collecting, updating, screening, maintaining, or analyzing fast-flowing data. Moreover, the *variety emphasis* of a BDV's innovation refers to the BDV's product focus on collecting, updating, screening, maintaining, or analyzing data from various sources and in different formats. Finally, we define the *veracity emphasis* of a BDV's innovation as the focus of the product on maintaining accuracy, correctness, and integrity of data available to a firm. We note that we do not define these areas of emphasis as mutually exclusive or collectively exhaustive. While a BDV can choose to emphasize neither or only one of the areas, another can emphasize more than one area.

Since the purpose of Big Data technologies is widely believed to be addressing the 4Vs challenges of Big Data (e.g., Lee et al. 2014), the effectiveness of a BDV's business model for an investing firm can be determined by the way the BDV's innovation emphasizes resolving these challenges. The more a BDV signals that its innovation is capable of resolving the challenges of Big Data, the morethe likelihood of its ability to create competitive advantage for investing firms

[3]Even if the investing firm is not the end customer of the BDV's product/service, the investors can gather economic benefits, i.e., through selling the product/service to end customers, and such economic gains depend on the value emphasis of the BDV's product/service.

is. Thus, variability in market returns of investment in BDVs can be explained by the extent of a BDV's business model emphasis on tackling the challenges of volume, velocity, variety, or veracity. Hence, we hypothesize that:

> H1a: The extent of a BDV's volume emphasis is positively associated with the market returns for the investing firm following the announcement of investing in the BDV.
>
> H1b: The extent of a BDV's velocity emphasis is positively associated with the market returns for the investing firm following the announcement of investing in the BDV.
>
> H1c: The extent of a BDV's variety emphasis is positively associated with the market returns for the investing firm following the announcement of investing in the BDV.
>
> H1d: The extent of a BDV's veracity emphasis is positively associated with the market returns for the investing firm following the announcement of investing in the BDV.

A BDV's Scope

Although the four value emphases mentioned above can all be regarded as important areas of focus for Big Data innovations, the existing literature on Big Data suggests that there is no agreement on the superiority of either of the emphases. Some experts suggest that some emphases are superior to others (e.g., Normandeau (2013) believes that emphasis on veracity is superior to other emphases), but mostly they regard the four areas of emphasis as equally important for handling the Big Data challenges (e.g., Jagadish et al. 2014). We suggest that the effectiveness of a BDV's value emphases is determined by the technological scope that its innovation operates at.

In the context of BDVs, we define the technological scope as the main Big Data area that the BDV's product/service is focused on. Big Data technologies cover diverse technological areas, most distinctively, Big Data security (McAfee and Brynjolfsson 2012), analytics applications (LaValle et al. 2013), and Big Data infrastructure (e.g., computing) (Jacobs 2009, McAfee and Brynjolfsson 2012). The review of the existing literature on Big Data suggests that Big Data technologies are also diverse in their architectural scope. While some Big Data technologies (e.g., cloud-based computing structures (Grossman and Siegel 2014)) are at the infrastructural level of IT architecture (see Weill and Vitale 2002 for a discussion of IT enterprise architecture), some technologies target the analytics application layer (e.g., data modeling applications (Grossman and Siegel 2014)). In addition to these more pronounced technological scopes, there is a third technological scope for Big Data innovations that is concerned with the security applications that protect large operations of the Big Data innovations belonging to the two other technological scopes. The following schema[4] presents the architectural schema that ties these three scopes together:

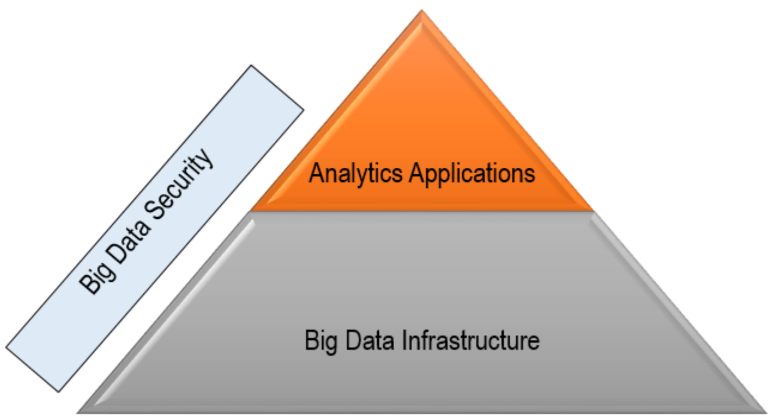


Figure 1- Architectural Relationship of Big Data Scopes

Jagadish et al. (2014) suggest a similar hierarchy for the Big Data operations that starts with data acquisition, storage, and integration at the infrastructural layer and ends with modeling and interpretation at the analytics application layer. They also mention the overarching role of Big Data security technologies that protect the infrastructural and application layers from potential data losses or breaches.

[4]This schema is adapted from Federal Deposit Insurance Corporation's (FDIC) enterprise architecture framework (OIG, 2005).

Since different scopes of Big Data technologies differ in their architectural position, their effectiveness can depend on different value emphases. For example, at the analytics scope, handling (i.e., sense-making of) data in different formats might be more crucial than it is at the infrastructural level where the data in different formats merely needs to be stored and integrated. As a result, a high variety emphasis in an analytics innovation might be more valuable than a high variety emphasis in an infrastructural one. Thus, we expect that the market returns on different Big Data value emphases varies across different technological scopes. Thereby, we hypothesize that:

H2a: The positive association between the extent of a BDV's volume emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the scope of BDV's innovation.

H2b: The positive association between the extent of a BDV's velocity emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the scope of BDV's innovation.

H2c: The positive association between the extent of a BDV's variety emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the scope of BDV's innovation.

H2d: The positive association between the extent of a BDV's veracity emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the scope of BDV's innovation.

Environmental Uncertainty of the Investing Firm

In addition to the characteristics of a BDV, i.e., its value emphasis and technological scope, the characteristics of the investing firm can also influence the payoffs for the investing firm. What is a lucrative investment for one firm might not be as beneficial for the other (Venkatraman and Prescott 1990). While internal characteristics can be important, the effect of the external environment of a firm is more salient with relation to BD investments. This is because Big Datatechnologies change the data focus of organizations from within-enterprise data (i.e., own suppliers, own firm, own customers) to outside-of-the-enterprise data (i.e., potential suppliers, potential customers) (Chen et al. 2012). The out-side-of-the enterprise data depends on the external environment of an organization. For example, the volume of data incoming for analytical purposes can directly depend on the number of competitors, the type of customers, number of products produced, etc. Further, velocity of incoming data can depend on the extent of dynamism in the environment. As an industry becomes more turbulent, the half-life of information decreases, requiring a firm increase the frequency of data-gathering. The resource-based view in IT suggests that environmental uncertainty, i.e., the extent of challenge and unpredictability in environment (Aldrich 1979; Child 1972; Pfeffer and Salancik 1978; Dess and Beard 1984), influences the payoffs IT investment create. Specifically, three dimensions of environmental uncertainty, dynamism, complexity, and munificence are highlighted.

Environmental dynamism is viewed as "the rate and unpredictability of environmental change" (Newkirk and Lederer 2006, p, 394). It represents the instability of the environment, which challenges managers to quickly and frequently adopt new strategies and tactics (Yayla and Hu 2012). Among the four BD value emphases, velocity is the most relevant to the dynamism aspect. As the extent of environmental dynamism increases, the half-life of external data for an organization decreases. In a vibrant environment, incoming data can lose its relevance faster, requiring an organization to increase the frequency at which it surveys, collects, and analyzes relevant data. As the frequency of collecting, storing, and analyzing incoming data increases, technologies with a value emphasis on velocity might be deemed more appropriable for firms in dynamic environments. Although we test for the interaction of all four value emphasis with the investing firm's environmental dynamism, we hypothesize, *a priori*, that:

> H3: The positive association between the extent of a BDV's velocity emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental dynamism of the investing firm.

Environmental complexity refers to "the heterogeneity and range of an industry and/or an organization's activities" (Wade and Hulland 2004, p. 127). Environmental complexity makes it difficult for managers to comprehend the drivers of performance (Newkirk and Lederer 2006). As the drivers of performance become more and more ambiguous for managers, the organizational need for accessing data starts to change. Ambiguity regarding success might be resolved through two paths. First, as the industry becomes more heterogeneous, the incoming data should match such heterogeneity. Therefore, BD investments that help access to a broader variety of data become more relevant and important. Aside from the emphasis on variety, emphasis on veracity can also help organizations facing a high degree of complexity. Due to the ambiguous nature of success and the need to access data from various sources, some of which might be of unknown nature, technologies with emphasis on data veracity can also be beneficial. As a firm increases its span of search for incoming data, authenticating information becomes more important. Although we test for the interaction of all four value emphases with the investing firm's environmental complexity, we hypothesize, *a priori*, that:

H4a: The positive association between the extent of a BDV's variety emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental complexity of the investing firm.

H4b: The positive association between the extent of a BDV's veracity emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental complexity of the investing firm.

Environmental munificence refers to the extent to which the firm's environment supports sustained growth (Dess and Beard 1984; Wade and Hulland 2004). Mature or shrinking environments generally have a low level of munificence, whereas rapidly growing markets are usually associated with a high level of munificence. In environments marked by low munificence, or hostile environments, stiff competition is usually present and adversely affects the accomplishment of organizational goals (Toole 1994). By contrast, munificent environments are more forgiving in natureand support organizational performance and growth despite inappropriate firm strategies (Wade and Hulland 2004). All four Big Data value emphases can become more beneficial as the environment of a firm becomes more hostile (i.e., less munificent). More hostile environments require more scanning of the environment and therefore access to more incoming data (volume), in greater frequency (velocity) and variety, with a greater need for data authenticity (veracity) as use of unauthenticated data can be more punishing. Therefore, we hypothesize:

H5a: The positive association between the extent of a BDV's volume emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental munificence of the investing firm.

H5b: The positive association between the extent of a BDV's velocity emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental munificence of the investing firm.

H5c: The positive association between the extent of a BDV's variety emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental munificence of the investing firm.

H5d: The positive association between the extent of a BDV's veracity emphasis and market returns for the investing firm following the announcement of investing in the BDV is moderated by the environmental munificence of the investing firm.

Methods

This research utilizes an event study approach. We define an event as the public announcement of a firm to invest in a BDV. The sample was formed by searching for related events from January 1st, 2010 to December 31st, 2013. An online search was conducted through the services of Lexis-Nexis by searching for public announcements made at all news sources available at Lexis-Nexis, containing the terms: (1) Big Data, and (2) investment, invest, acquiring, or acquire, and (3) venture, new venture, or start-up. The search resulted in 3,239 related news pieces. Upon further refinement of this set, 1393 news pieces were identified as the ones that a firm has invested in a BDV. These related news articles were then further refined by excluding announcements where: (1) there was a confounding announcement related to the firm (e.g., major earnings, change in top executives, mergers, etc.) in a window of five days before and after the BDV announcement, (2) there was more than one investment in a BDV in a 300-day period prior to the announcement, (3) the firm was non-US, not-for-profit, or sub-division of a bigger firm, or (4) the firm was not publicly traded, or the study's organizational controls were not available. This process resulted in a set of 651 public announcements in our final set[5].

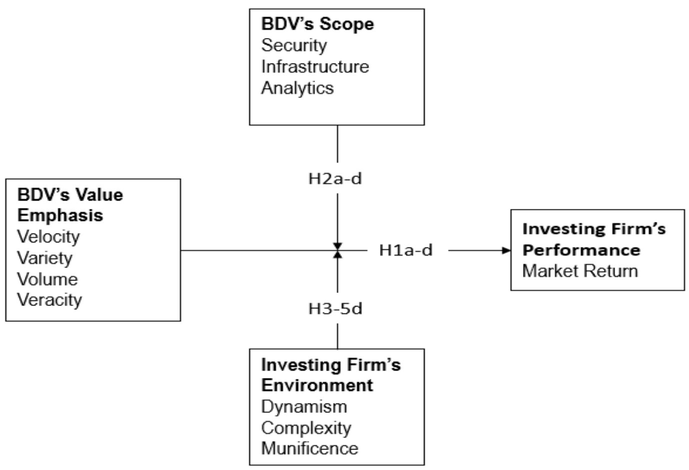


Figure 2- Research Model

Measures

Value Emphasis

In order to determine the volume, velocity, variety, and veracity emphases of a BDV's business model, we conducted a text analysis of the product description section of the BDV's webpage. We believe a BDV's value emphases can be unfolded in the product description section of the BDV's webpage because that section is the medium through which the product is

[5]Appendix A includes an illustrative example of an announcement.

introduced and its potential superiorities to competing products is explained. The webpage associated with the BDV was crawled using the hyperlinks embedded in each announcement's news pieces[6]. In cases where the hyperlink to the BDV's webpage was not embedded in the announcement's news piece, a manual search was conducted to find the webpage. The text-mining module of R (tm) was used to analyze the product description section of each BDV's website. In order to do so, first, a set of words associated with each of the four areas of emphasis was compiled using the existing literature on Big Data technologies. We searched *Google Scholar* for 2010-2103 articles that contained terms: (1) Big Data, and (2) volume, velocity, variety, or veracity. Over 1300 articles were identified, and the HTML version of these articles were combined to form a corpus.

This corpus was text-mined to extract sentences that did not include any of the words volume, velocity, variety, or veracity, with the exception of sentences that were adjacent to the sentences containing these words. Then, the sentences containing the 4Vs and their adjacent sentences were analyzed to form a network of bigrams[7] (i.e., combination of two words) that are closely associated with handling the 4Vs. For example, the bigrams "accelerated computing", "fast response", and "real time" had the highest frequency of occurring when the word "velocity" was discussed in the corpus of articles. Also, the bigrams "large size", "massive data", and "large calculations" were among the most used adjacent words to "volume". Further, the bigrams "multimedia data", "different formats", "non-textual data", and "unstructured data" were used adjacent to the word "variety." Finally, "data authentication", "data cleansing", and "data verification" were adjacent to the word "veracity". The adjacent bigrams were then processed to

[6]Only descriptions with a time stamp prior to the announcement were used in the analysis.
[7]We use bigrams instead of single words, because combination of two words more accurately point to a concept, as opposed monograms (i.e., single words) (e.g., Faraj et al. 2015).

eliminate the ones that are irrelevant to the concepts of 4Vs[8]. Then, a library of refined bigrams for each of the 4Vs were used to analyze the product description section of each BDV in the sample. For each of the four emphases, we calculated the frequency of its associated bigrams in the product description corpus of text. Then, we obtained the ratio of associated bigrams to the total number of bigrams in the text as the measure of each of the 4 emphases. For example, if the product description of a BDV contains 2 bigrams associated with "volume" and the text contains 200 meaningful bigrams in total, then the value of the volume emphasis is 0.01 (=2/200).

Technological Scope

We used the product description section part of a BDV's webpage to determine the technological scope at which it operates. We searched the description for the words "analytics" and "intelligence" to categorize the BDV's innovation in the scope of analytics. If the words "security" or "cyber-security" were used in the description, the innovation was categorized in the security scope, and descriptions with the words "infrastructure", "cloud", "computing", and "grid" were categorized in the infrastructure scope. Out of 651 BDVs in the sample, our analysis resulted in identification of 427 BDVs with a clear categorization (the searched words were used in the description and the BDV could not be categorized in two or more scopes). The rest of the 224 BDV descriptions were manually read and categorized into the three scopes of Big Data technologies. To ensure the validity of manually categorized ventures, a sub-set of BDVs which

[8]We retained only bi-grams that appeared in at least 10% of the relevant articles. Appendix B presents the results of the main model where the bi-grams appearing in 5% and 20% of the relevant articles are considered. Although these bi-grams were used in academic articles adjacent to the 4Vs concepts, we asked a panel of four tenured Management Information Systems professors from a public school in mid-west US to evaluate (very good, good, fair, poor) the correspondence of each bi-gram to the concept it describes (i.e., volume, velocity, variety, or veracity). Rater agreed in their rating of 63 (85%) of the big-grams. Out of the 74 bi-grams, eight did not pass Obermiller and Spangeberg's (1998) threshold of having at least three raters evaluating the bi-gram very good and no poor evaluation. Model B3 in Appendix B presents the results of the model with these words dropped from the calculations of the 4Vs.

had a presence in *AngelList.com* a crowd-funding service were selected (149 out of 224). *AngelList* reports the technological scope tag of the registered BDVs (i.e., if the BDV is active in the area of analytics, Big Data infrastructure, or Big Data security). We compared the reported tags of those 149 BDVs with our manual categorizations. It resulted in 138 matched cases, showing a reliability of 92.6%.

Inclusion of technological scopes as a co-variate along with the value emphases poses a potential threat. That is, BDVs in certain scopes may emphasize certain aspects of Big Data challenges more than the others. If that is correct, a BDV's value emphases may be correlated with its technological scope, hence making the estimates of value emphases endogenous. To test for such potential threat, we compared the means of each value emphasis across the three scopes of Big Data in our sample. The analysis of variance (ANOVA)[9] for difference of the value emphases across the three scopes fails to reject the null hypothesis about that assumes the scope of a BDV does not influence its emphasis on tackling the 4Vs of Big Data (Velocity: F-statistic= 0.617, p-value = 0.540; Variety: F-statistic= 0.861, p-value = 0.423; Volume: F-statistic= 1.294, p-value = 0.275; Veracity: F-statistic= 2.599, p-value = 0.075).

Environmental Uncertainty

The three dimensions of environmental uncertainty are measured using prior measures and COMPUSTAT data. Following the prior literature (Keats and Hitt 1988; Xue et al. 2011), we measure **environmental dynamism** by quantifying the volatility of industry sales. For each firm, the natural log of total sales of four-digit SIC industry to which a firm belongs is regressed against an index variable of years, for a period of five years [t, t-4], and the antilog of the standard error of the regression coefficient is used to measure sales volatility as a proxy of a

[9]For each of the value emphases (e.g., emphasis on volume) we compared the mean score across the three scopes of analytics, security and infrastructure.

firm’s environmental dynamism. We measure **environmental complexity** using the reciprocal of industry concentration. This is consistent with the logic that firms situated in industries with fewer competitors (i.e., more concentration) is embedded in less complex environment where the competitors and their likely actions are well known. Specifically, following Xue et al. (2011), the log value of the reciprocal of the Herfindahl index of the market shares of the top four firms in that industry (i.e., the sum of the squares of the market shares of the four firms with the highest sales in that industry) is used to measure environmental complexity. Following prior literature (Keats and Hitt 1988; Xue et al. 2011), **environmental munificence** is measured based on growth in industry’s sales. To do so, the natural log of total sales of four-digit SIC industry to which a firm belongs is regressed against an index variable of years, for a period of five years [t, t-4]. The antilog of the regression coefficient is then used to measure munificence.

Market Return

Following the existing literature on event studies (e.g., Chatterjee et al. 2001; Xu and Zhang 2013), we use cumulative abnormal return (CAR) as a measure of market returns to investments in BDVs. CAR measures unexpected market returns in a window of time around an announcement when the news release of the investment is supposed to be followed by a market reaction. When CAR is positive, it reflects that the announcement has been met with a positive reaction in the market and thereby the market returns exceed the expectation. A zero CAR shows indifference in the market with regards to the announcement, and a negative CAR shows a negative reaction from the market. To calculate the normal returns, we first calculate the market model which is:

$$R_{i,t} = \alpha_i + \beta_i * R_{m,t} + \epsilon_{i,t}$$

Where $R_{i,t}$ is return on stock i in day t, and $R_{m,t}$ is the return on market portfolio on day t. α_i and β_i are regression estimates for firm i and $\epsilon_{i,t}$ is the error term for the regression. The market portfolio is calculated using equally-weighted *CRSP* index for the main analysis, and value-weighted index is used in a robustness check. Following the previous literature (e.g., Sabherwal and Sabherwal 2007; Chatterjee et al. 2001), the market model was estimated using a 255-day window starting from 300 days before the announcement to 46 days before it. The normal return was calculated by $\alpha_i + \beta_i * Rm, t$using the coefficient estimates of the market model. Then abnormal return (AR) was calculated as:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i * Rm, t)$$

This abnormal return was then cumulated over a 3-day window (i.e. one day before the day of announcement, and one day after announcement [-1, +1]). Since it is possible that market reacts in a wider span of time to the announcement, we also calculate CAR in a 5-day (i.e., [-2, +2]) window for further robustness checks.

Controls

We controlled for the fixed effect of **industry** of the investing firm by including an industry dummy generated from 2-digit SIC code associated with the firm. Moreover, to account for the effect of possible time trends, we created a variable called **time** that accounts for the number of days between January 1st, 2010 and the date of the announcement. Further, we control for the **firm size** by using the natural log of total assets ($) of the investing firm, collected form *COMPUSTAT*. Finally, we account for the intensity of the investment made by creating a variable called **investment value** that uses the natural log of the value ($) of the investment made in each announcement.

Further, during the data collection, we noticed that while some investments in BDVs are made in the form of a partnership where the investing firm contributes to the seed funding of a BDV, some investments are made to acquire the BDV. Since acquiring a BDV has distinct difference in governance and transfer of risks and benefits of the BDV to the investing firm, it is plausible to assume that CAR for acquiring firms can be different from the rest of the sample. Therefore, we created an "**Acquired**" dummy (1 if the investing firm acquired the BDV; 0 otherwise) to control for potential effects.

Moreover, while some investing firms become the end-users of the BDV for their core activities, whereas some may utilize the BDV's product/services for operational purposes. For example, a banking corporation might invest in a BDV active in detecting credit-card breaches. In such an example, the product/service of the BDV aligns with the main activity of the investing firm. On the contrary, a retailing company might invest in a BDV that offers an analytical visualization service. In this example, the BDV's product/service is used for enhancing internal operations of the investing firm. Therefore, the relevance of a BDV's product/service to an investing firm may affect the way that the market evaluates such investments. Hence, we created a "**main**" dummy (1 if the investing firm uses the BDV's product/service for its main activity; 0 otherwise) to control this effect. Each BDV reports the industry of end-users through a secondary tag in its AngelList page. We compared the industry of a BDV's end-user to the industry of the investing firm. In case of a match, we assume that the BDV's product/service is used to perform a main activity in the investing firm.

Finally, although we control for the time trends in our model, it can be argued that occurrence of a specific economic or technological event in a certain year, if not accounted for, can bias the coefficient estimates. To overcome this threat, we followed the suggestions of Greene (2011) and controlled for each year's fixed effect by including **year dummies** (2010 was the reference year) in the estimation model.

Model and Estimation

In order to test for our first set of hypotheses (H1) we first formed a direct effect model with CAR of announcement *i* as the dependent variable and the four value emphases, i.e., volume, velocity, variety, and veracity, along with the BDV's scope dummies, analytics and security (we use the Infrastructure scope as the reference group) as the independent variables, while controlling for the controls mentioned above:

$$CAR_i = \alpha_0 + Controls + \beta_1 * (Velocity) + \beta_2 * (Variety) + \beta_3 * (Volume) + \beta_4 * (Veracity) + \beta_5 * (Analytics) + \beta_6 * (Security) + \epsilon_i$$

We estimate this model using an ordinary-least-squares (OLS) estimation. However, since there are instances of a firm investing in more than one announcement, we estimate robust variance of coefficients by allowing the error terms of investments made by the same firm be correlated. Then, to test the second set of hypotheses (H2) we first follow an interaction approach and run the following estimation, while mean-centering the emphases variable (continuous variables) following the suggestions of (Cohen et al. 2013).

$$CAR_i = \alpha_0 + Controls + \beta_1 * (Velocity) + \beta_2 * (Variety) + \beta_3 * (Volume) + \beta_4 * (Veracity) + \beta_5 * (Analytics) + \beta_6 * (Security) + \beta_7 * (Velocity) * (Analytics) + \beta_8 * (Variety) * (Analytics) + \beta_9 * (Volume) * (Analytics) + \beta_{10} * (Veracity) * (Analytics) + \beta_{11} * (Velocity) * (Security) + \beta_{12} * (Variety) * (Security) + \beta_{13} * (Volume) * (Security) + \beta_{14} * (Veracity) * (Security) + \epsilon_i$$

As an alternative approach, we also run a split-sample analysis where we compare the below model across the three scopes of analytics, security and infrastructure:

$$CAR_i = \alpha_0 + Controls + \beta_1 * (Velocity) + \beta_2 * (Variety) + \beta_3 * (Volume) + \beta_4 * (Veracity) + \epsilon_i$$

In order to test for hypotheses 3-5, the following model will be tested[10]:

[10]The environmental variables, dynamism, complexity, and munificence are measured in the same year as the announcement. The measures of emphasizing 4Vs are collected from the product descriptions posted prior to the announcement and in the same year.

$$\text{CAR}_i = \alpha_0 + \text{Controls} + \beta_1 * (\text{Velocity}) + \beta_2 * (\text{Variety}) + \beta_3 * (\text{Volume}) + \beta_4 * (\text{Veracity}) + \beta_5 * (\text{Analytics}) + \beta_6 * (\text{Security}) + \beta_7 * (\text{Velocity}) * (\text{Analytics}) + \beta_8 * (\text{Variety}) * (\text{Analytics}) + \beta_9 * (\text{Volume}) * (\text{Analytics}) + \beta_{10} * (\text{Veracity}) * (\text{Analytics}) + \beta_{11} * (\text{Velocity}) * (\text{Security}) + \beta_{12} * (\text{Variety}) * (\text{Security}) + \beta_{13} * (\text{Volume}) * (\text{Security}) + \beta_{14} * (\text{Veracity}) * (\text{Security}) + \beta_{15} * (\text{Velocity}) * (\text{Dynamism}) + \beta_{16} * (\text{Variety}) * (\text{Dynamism}) + \beta_{17} * (\text{Volume}) * (\text{Dynamism}) + \beta_{18} * (\text{Veracity}) * (\text{Dynamism}) + \beta_{19} * (\text{Velocity}) * (\text{Complexity}) + \beta_{20} * (\text{Variety}) * (\text{Complexity}) + \beta_{21} * (\text{Volume}) * (\text{Complexity}) + \beta_{22} * (\text{Veracity}) * (\text{Complexity}) + \beta_{23} * (\text{Velocity}) * (\text{Munificence}) + \beta_{24} * (\text{Variety}) * (\text{Munificence}) + \beta_{25} * (\text{Volume}) * (\text{Munificence}) + \beta_{26} * (\text{Veracity}) * (\text{Munificence}) + \epsilon_i$$

Results

Table 1 provides a summary of descriptive statistics. Our sample shows that the average value of investment in BDVs is around 0.02% of the firm's annual sales. Also, on average, investing in a BDV results in a 0.31% cumulative abnormal return, while this number can be as low as -17.4% and as large as over 16.5%. The average size of an investing firm's total assets in our sample is slightly over $18 billion, with largest investing firm in the sample showing an asset endowment as large as $62.9 billion. Table 2 reports the results of our full-sample and sub-sample analysis. Model 1 in Table 2 reports our direct effect model where we find that the investment value has a positive and significant effect on CAR ($P<0.001$). This means that the size of abnormal returns increase as firms increase the intensity of their investment in a BDV. This results suggest that in spite of described cautions about Big Data investments and their associated risks (e.g., Jacobs 2009; Lazer et al. 2014), the market reacts positively to a firm's decision for sizable investments in BDVs.

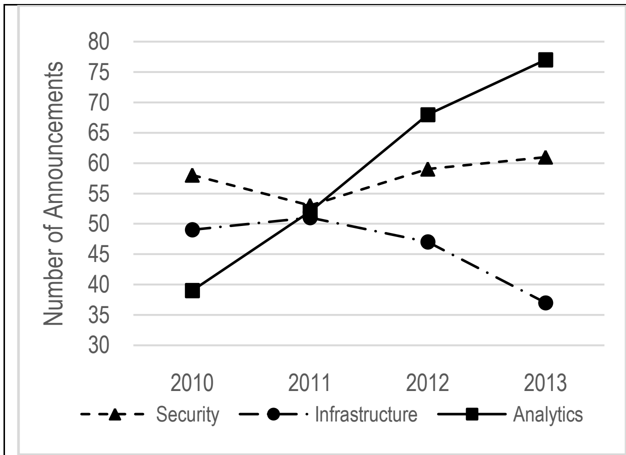
Moreover, Model 1 suggests a positive and significant effect of firm size on CAR ($P<0.01$). This means that a larger firm's investment in BDVs is met with more positive reaction in the market. Also, the positive and significant sign of the Analytics scope ($P<0.05$) and Security scope ($P<0.01$) dummies suggest that investment in these two scopes is perceived more beneficial than investment in Big Data infrastructures. Further, the non-significance of the Time dummy suggests that the market reactions to investments in BDVs do not change over time, at least when the full sample is considered. Finally, the results point to positive and significant effects of a Volume ($p<0.01$), Velocity ($p<0.01$), Veracity ($p<0.05$), and Variety ($p<0.05$) emphasis in a BDV's business model. This suggests that the market positively reacts to focus of a BDV on either of the Big Data 4Vs and that, explication of such focus in product description of a BDV positively affects their perceived value in the market, supporting H1a-d.

---Insert Tables 1 and 2 here---

Model 2 in Table 2 tests for the moderating effect of a BDV's technological scope on the impact of its value emphases. The positive and significant coefficient estimate for the interaction between the Analytics dummy and Variety ($p<0.001$) (supporting H2c) or Veracity ($P<0.01$) (supporting H2d) emphasis suggests that a focus on overcoming variety or veracity issues of Big Data is more beneficial for analytics innovations than it is for Big Data infrastructure. Moreover, the positive and significant estimate of the coefficient for the interaction between the Security and Veracity emphasis ($p<0.001$) (supporting H2d) suggests that a focus on tackling the veracity of Big Data is perceived more beneficial for Big Data innovations in the scope of security compared to infrastructure. Also, the non-significance of interaction coefficients between Analytics or Security, and the emphasis on Volume or Velocity suggests that an emphasis on the volume and velocity of Big Data is regarded as equally beneficial across the three scopes of Big Data innovations.

In order to gain a better understanding about the market returns of emphasizing the 4Vs, and given the apparent heterogeneity across the three Big Data scopes, we continue our analysis by dividing the samples into three sub-samples. Model 3 reports the analysis of our data for announcements that are made on a BDV active in the scope of security. Similar to the full-sample analysis, both investment value and firm size positively and significantly affect CAR, while no apparent change in the market return over time is traceable. Also, an emphasis on volume, velocity, or veracity shows a positive and significant effect, however, an emphasis on variety does not increase CAR in the security scope. On the other hand, Model 4 that reports the results for the sub-sample of announcements in the infrastructure scope shows a negative and significant effect of the Time dummy ($p<0.05$) suggesting that from 2010 onwards the perceived value of Big Data infrastructure in the market has been decreasing. Also, Model 4 indicates that only an emphasis on volume or velocity positively and significantly affects CAR, whereas there is no support for the effect of emphasis on variety or veracity in the infrastructural scope of BDV innovations. Finally, Model 5 shows the estimation of the model for the subsample of announcements that are made on BDVs active in the analytics scope. Contrary to the infrastructural scope, the positive and significant effect of the Time dummy ($p<0.05$) suggests that over time, market returns to investment in analytics innovations have improved. Moreover, the results of analysis in this subsample suggests that an emphasis on any of the 4Vs in the analytics scope is associated with higher CAR.

To shed more light on the observed market-return trends, we plotted the number of investments made in each scope (Figure 3a), as well as the average CAR (Figure 3a) from 2010 to 2013. These plots further corroborate the trends revealed in Models 3-5. The plots show that the popularity and market returns on BDVs active in the security scope have remained steady across the four years of the study, whereas the popularity and market returns of BDVs active in infrastructure and analytics have followed contrasting patterns. While BDVs in analytics scope have seen a raise in popularity and value, those in the infrastructure scope have endured a slight drop. These results further indicate the heterogeneity of patterns across the different technological scopes of Big Data innovations.



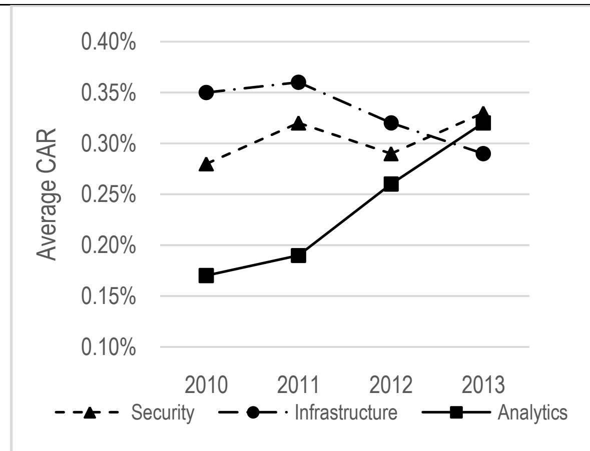


Figure 3a- Number of Announcements per Scope	**Figure 3b- Average CAR per Scope**

Robustness Tests

In order to make sure the results are robust to variations in measurement of constructs and selected control variables, we conducted a series of robustness checks. Table 3 reports the results of these first sets of analysis. First, we cumulated abnormal returns over a 5-day period (i.e., [-2, +2]) instead of a three day (i.e., [-1, +1]) period (Models 6-8). Then, instead of using an equally-weighted index of *CRSP* in calculating the market returns, we used a value-weighted index. Models 9-11 report the results with CARs calculated based on the value-weighted index for estimating market returns. Further, Models 12-14 report the sub-sample analysis models for an alternative measure of emphasis on the 4Vs. In these models, instead of measuring the BDV’s emphasis on the 4Vs through assessing the product descriptions posted on the BDV’s website, we analyzed third-party’s blog reports on the BDV’s product. For doing so, a blog covering the

BDV's innovation was identified through a Lexis-Nexis search[11] and then, the blog's description of the product was analyzed in the same manner to obtain the extent of the BDV's emphasis on any of the 4Vs. We did so, because there might be doubts regarding the accuracy of claims made by a BDV on its website. Evaluating the product's emphases through a third-party report can reduce the concern that self-presentation of the product might involve exaggerations that affect the accuracy of our measures. The results of models presented in Table 3 qualitatively converge with the results of Models 3-5, providing evidence for robustness of our findings to variations in measurement of key constructs.

---Insert Table 3 here---

The Effect of Environmental Uncertainty

We also tested for the moderating effect of environmental uncertainty, while keeping the interactions of technological scope and value emphasis in the model. Table 4 summarizes the results when the interaction of value emphasis and environmental uncertainty variables are included. Model 15 presents the results of a direct effect model, whereas Model 16 reports the results with the interaction terms included. Consistent with H3, a positive and significant interaction between Dynamism and emphasis on Velocity is observed ($p < 0.001$). Also, the findings suggest that interaction of other value emphases with Dynamism is insignificant. Moreover, consistent with H4a and H4b, both Variety ($p < 0.001$) and Veracity ($p < 0.01$) show significant and positive interaction with Complexity, while the interactions of Velocity and Volume with Complexity are insignificant. Finally, Velocity ($p < 0.05$), Variety ($p < 0.01$), Volume ($p < 0.001$), and Veracity ($p < 0.05$) emphases show a negative and significant

[11]In cases where more than one blog covered a report describing the BDV's product, we selected the blog post with more words, because of its higher potential for reflecting on the value emphases of the product.

interaction with Munificence, consistent with H5a-H5d. Models 17-19 report the results when: a 5-day window, value-weighted measure of CAR, and alternative measures of 4Vs based on blog posts (instead of the product/service description written by the BDV) are considered in estimations. These models present results that qualitatively converge with findings in Model 16.

---Insert Table 4 Here---

Payoffs for the BDV

While the role of value of emphasis and technology scope in creating value for the investing firm is investigated, we complement our analysis by finding out if the two factors can benefit the BDV itself. Raised capital is viewed as an early financial success indicator for new ventures in early stages. We investigate if the value emphases of a BDV contribute to its success in raising capital. Also, we test if such an effect is moderated by the technological scope of the innovation. To do so, we focus on BDVs active in AngelList.com, and track their raised capital in each round of fundraising. This analysis focuses on 2,026 BDV-round observations, belonging to 529 unique BDVs. On average, each BDV had raised a total of $4.62 million, had 12.42 employees, and 24.58% of them were ultimately acquired by a larger firm. For each round, the value emphasis on each of the Big Data 4Vs is calculated similar to the previous section, however, the corpus of text analyzed to determine each emphasis is limited to the content generated within each round. Raised capital and dates indicating the beginning and ending of each fundraising round is crawled from AngelList.com. For each BDV, the technological scope is evaluated similar to the previous section.

Additionally, we control for the stage of development where the funding is raised. We do so because early and late stages of fundraising are different in terms of funding providers, as well funds needed. To best capture the effect of fundraising stage, for each stage of development (e.g., seeding, stage A) we specify a variable, where the value of variable indicates number of fundraising rounds a new venture has completed in that stage prior to the current round. Therefore, for BDVs in their first round of fundraising, the value of seeding, stage A, stage B, and stage B variables is 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.

Also, we control for the number years since a BDV has been established because the time elapsed since establishment of a venture can have an effect on resources it can access, both financially and intellectually. We control for the location dummy, measured at the city level, and whether or not the venture identifies itself as a business-to-business or business-to-customer (identified by tags reported in AngelList.com). Moreover, number of employees[12] (including co-founders) in the fundraising period of interest, and average of employees (including co-founders) value of education[13] are controlled for. Table 5 presents the results for the effect of emphasis on BD 4Vs in the full sample (Model 20), as well as in the sub-samples representing each technological scope (Models 21-23).

---Insert Table 5 here---

The results mainly converge with those pertaining to payoffs for the investing firm, suggesting that BDVs which are focused on infrastructural technologies see an increase in their raised capital when they emphasize the aspects of Volume and Velocity, whereas for BDVs

[12] AngelList reports the date of employment and departure of employees. This data was used to calculate number of employees employed in each fundraising period.

[13] The LinkedIn account of each employee was accessed to obtain educational background of employees. The highest degree obtained by each individual was then coded (high school diploma=1, associate degree= 2, undergraduate degree= 3, master's degree= 4, doctorate= 5) and averaged for each BDV.

active in the scope of security, emphasizing Veracity is also beneficial. Finally, BDVs active in the scope of analytics benefit from emphasizing all 4V aspects of Big Data. Together, the results suggest that BDVs benefit from the value emphasis of Big Data 4Vs in the same fashion that the investing firms do.

Discussion

Motivated by the rather unknown factors that influence the economic success of investment in Big Data innovations, this study has focused on a prevalent mode of investment, i.e., investment in BDVs. While there has been a void in studying general investments in new IT ventures, the issue is more amplified in the context of Big Data given the understudied nature of Big Data technologies. Investment in BDVs as a way of organizational investment in Big Data has emerged as a phenomenon of interest for the IS field. Following an event-study approach, this paper has focused on the role of the BDV's business model as the driver of market returns for investing firms. Specifically, we focus on the value emphasis component of a BDV's business model. Given the purpose of Big Data innovations in solving the challenges of 4Vs (i.e., velocity, volume, variety, and veracity), we proposed a framework to make sense of a BDV's value emphasis by considering its focus on overcoming the 4Vs challenges. In other words, we contend that BDVs propose creating value for their investors through addressing the 4V challenges of Big Data. Moreover, building on the existing literature on Big Data (e.g., Jagadish et al. 2014), we suggested that Big Data innovations can be heterogeneous in terms of the effectiveness or novelty of emphasis on 4Vs. As a result, we hypothesized that some areas of emphasis may not be met with increased market returns in certain scopes.

We took a longitudinal approach to study investments in BDVs from 2010 to 2013. Focusing on investments made by publicly-traded firms, we found that, in general, as a BDV increases its emphasis on overcoming any of the 4V challenges, the market returns for its investors increase. Nonetheless, our results point to a heterogeneity in the value of these 4 areas of emphasis. Across the three technological scopes of Big Data, an emphasis on overcoming the issues of volume or velocity of data proves beneficial consistently. However, an emphasis on overcoming the issue of data veracity only becomes important for Big Data security or analytics innovations. Also, an emphasis on overcoming the issue of data variety meets abnormal market returns only in the scope of analytics. Although the existing literature on Big Data points to the 4Vs in a flat manner, where the four issues are almost regarded equivalently, our findings point to a heterogeneity in the value of the four areas of emphasis. This heterogeneity matches our proposed hierarchy of Big Data technological scopes. That is, parallel to the architectural hierarchy of Big Data technologies, there exists a hierarchy of challenges.

Figure 4 depicts the hierarchy of challenges along with the architectural hierarchy of Big Data technologies presented earlier. As it can be seen, at the infrastructural layer, emphasis on harnessing the volume and velocity of data is vital. Moving up the pyramid, veracity becomes important when fast-responding security algorithms also require detection of anomaly in data and verifying sources of the data (e.g., LaValle et al. 2013) to function well. Finally, at the analytics application layer, handling massive loads of data on the fly, along with the capability to leaving out unreliable data, is important, but also, utilizing and sense-making of data that comes in various formats becomes of paramount value. We note that our proposed hierarchy of emphasis does not suggest that overcoming the issues of veracity or variety of data are not needed at all at the infrastructural layer of architecture. For example, if Big Data structures are not capable of collecting and storing data in various formats and form different sources, they cannot deliver on their promise. Rather, the hierarchy means that not all of the areas of emphasis are of the same importance or ability to create competitive advantage for investing firms.

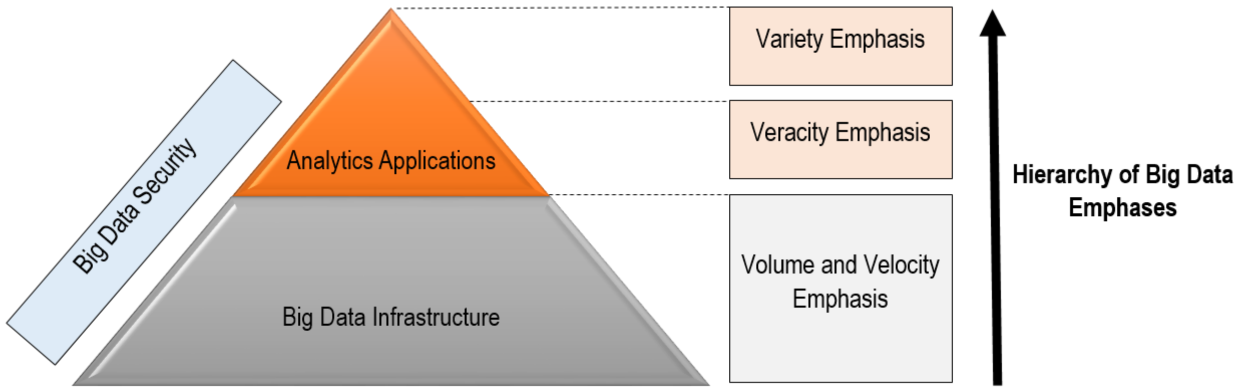


Figure 4- Architectural Hierarchy of Big Data Emphases and Scopes

In addition to the moderating role of the technological scope, we recognized that the environmental uncertainty of the investing firm also influences the effect of value emphases. Specifically, we find that for firms active in the dynamic environment, investing in BDVs that emphasize the velocity aspect of Big Data becomes more beneficial, whereas for firms active in a complex environment, investing in BDVs that focus on variety and veracity is met with more payoffs. Finally, we found that firms that are active in more hostile environments obtain benefits from an emphasis on either of the 4V aspects of Big Data.

The findings of this study should be seen in the light of its ***limitations***. First and foremost, our study has focused on publicly-traded firms and thereby our insights are limited to only a subset of firms that engage in making investments in BDVs. Because of their relatively larger size, competition dynamics and performance implications can be different for publicly-traded firms compared to the smaller or privately-owned organizations. Moreover, market-based measures of performance, such as CAR, are limited in considering insiders' insight and foresight (e.g., Sabherwal and Sabherwal 2007) about the investment. However, given the recentness of the investments in our sample (2010-2013) and the fact that the investments are made in innovations that are at the early stages of development, productivity measures of firm performance cannot be much informing either. We suggest that future research can examine the productivity of these investments once enough time has elapsed to observe and measure performance effects of these investments more directly. Also, due to the secondary nature of our data, our measures of value emphases are limited to insights that can be gathered from product descriptions announced by the BDV. Product descriptions written by BDVs may be biased. Although we have made efforts to triangulate our findings by assessing these emphases from third-party reports, a BDV's emphases on addressing 4Vs of Big Data could be measured with more objective alternatives. Finally, our data is limited to identify the mechanisms through which product/services of a BDV are utilized by investing firm. While some firms may utilize a BDV's product/service to enhance their core competencies, others might utilize it for more peripheral purposes such as maintenance and security. Our findings should be interpreted while considering the heterogeneous uses of BDV products which this study could not account for.

In spite of its limitations, this study has ***theoretical contributions*** to the field of IS. First, this study extends the current literature on the business value of IT investments by offering a lens to assess the value of investments made on new ventures. Specifically, this study extends the use of a business model lens to studying the value of investment in IT ventures. Moreover, unlike the prevalent unilateral focus on the value emphasis portion of a business model (e.g., Brynjolfsson et al. 2010; Lin et al. 2012), this study highlights the importance of considering the technological scope of an innovation in explaining the value-adding mechanisms of business models. Second, this study provides a more nuanced view of the 4V challenges of Big Data and incorporates them in a framework to make sense of the relationship between overcoming these challenges and making competitive advantage for a firm. This study shows that emphasizing these four areas of challenge can make firms competitive, although the effects of these emphases is contingent upon the nature (i.e., scope) of the innovation. Thereby, the findings of this study suggest that the competitive value of overcoming each of the 4Vs depends on the technological scope in which an organization needs to invest. Third, by showing a general positive CAR as a result of investment in BDVs, this study sheds light on the discussions regarding the risky nature of Big Data investments (e.g., Jacobs 2009; Lazer et al. 2014). This study provides evidence that in spite of the existing risks, firms benefit by engaging in Big Data innovations, especially when these investments are made in the form of funding new ventures.

In addition to its theoretical contributions, this study provides some ***practical implications***. The findings of this study inform the organizational decision-makers by providing them with a framework to assess the likely value of investing in BDVs. Table 6 presents our contingency framework for investors where depending on the scope of their investment, they can evaluate the promise of a BDV by assessing its emphasis on overcoming the relevant issues of volume, velocity, variety, or veracity. Specifically, our results suggest that investing mangers can assess the value emphases of BDVs either by reviewing the product description offered by the BDV itself, or by reviewing reports about the BDV in blogsphere. Moreover, our findings suggest that larger firms, as well as those that make bigger investments in BDVs, can expect more market payoffs from their investments.

Finally, our results suggest that investing firms must evaluate the value emphases of a BDV with regards to the industrial uncertainty they face. Our findings indicate that firms in hostile environments can gain more benefits from an increased emphasis on either of the 4V aspects of Big Data. Moreover, our results suggest that firms in dynamic environments can increase their gains by investing in BDVs that emphasize overcoming the issues of handling high velocity of data, whereas, those in complex environments must direct their investments into BDVs that emphasize the aspects of variety and veracity. Also, our findings suggest that investors can increase their returns by acquiring BDVs instead of providing a limited investment without further integration of the BDV into their organization. Finally, our findings can inform Big Data entrepreneurs and founders of new BDVs, by suggesting that their market attractiveness can increase if they explicate their emphases in overcoming the 4V challenges of Big Data. Our results show that product descriptions of a Big Data innovation, operates as a medium to communicate the product's value-generating emphasis. Therefore, we encourage BDV founders to better explicate the value of their innovation by highlighting the role it plays in controlling the volume, velocity, variety, or veracity of Big Data.

References

Afuah, A., and C. L. Tucci. 2000. *Internet Business Models and Strategies: Text and Cases*, McGraw-Hill Higher Education.

Agarwal, R., and V. Dhar. 2014, "Editorial—Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research," *Information Systems Research* (25:3), pp. 443-448.

Aldrich, H. E. 1979. Organizations and Environments, Prentice Hall, Englewood Cliffs, NJ.

Al-Debei, M. M., and D. Avison. 2010, "Developing a Unified Framework of the Business Model Concept," *European Journal of Information Systems* (19:3), pp. 359-376.

Amit, R., and C. Zott. 2001, "Value Creation in e-business," *Strategic Management Journal* (22:6-7), pp. 493-520.

Bharadwaj, A., O. A. El Sawy, P. A. Pavlou, and N. Venkatraman. 2013, "Digital Business Strategy: Toward a Next Generation of Insights," *MIS Quarterly* (37:2), pp. 471-482.

Bonaccorsi, A., S. Giannangeli, and C. Rossi. 2006, "Entry Strategies Under Competing Standards: Hybrid Business Models in the Open Source Software Industry," *Management Science* (52:7), pp. 1085-1098.

Brynjolfsson, E., and L. M. Hitt. 2000, "Beyond Computation: Information Technology, Organizational Transformation and Business Performance," *The Journal of Economic Perspectives* (14:4), pp. 23-48.

Brynjolfsson, E., P. Hofmann, and J. Jordan. 2010, "Cloud Computing and Electricity: Beyond the Utility Model," *Communications of the ACM* (53:5), pp. 32-34.

Casadesus-Masanell, R., and G. Llanes. 2011, "Mixed Source," *Management Science* (57:7), pp. 1212-1230.

Casadesus-Masanell, R., and J. E. Ricart. 2010, "From Strategy to Business Models and Onto Tactics," *Long Range Planning* (43:2), pp. 195-215.

Chatterjee, D., V. J. Richardson, and R. W. Zmud. 2001, "Examining the Shareholder Wealth Effects of Announcements of Newly Created CIO Positions," *MIS Quarterly* (25:1), pp. 43-70.

Chen, H., R. H. L. Chiang, and V. C. Storey. 2012, "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly* (36:4), pp. 1165-1188.

Child, J. 1972, "Organizational Structure, Environment and Performance: The Role of Strategic Choice," *Sociology* (1), pp. 2-22.

Cohen, J., P. Cohen, S. G. West, and L. S. Aiken. 2013. *Applied Multiple regression/correlation Analysis for the Behavioral Sciences,* Routledge.

Demirkan, H., and D. Delen. 2013, "Leveraging the Capabilities of Service-Oriented Decision Support Systems: Putting Analytics and Big Data in Cloud," *Decision Support Systems* (55:1), pp. 412-421.

Deodhar, S. J., K. Saxena, R. K. Gupta, and M. Ruohonen. 2012, "Strategies for Software-Based Hybrid Business Models," *The Journal of Strategic Information Systems* (21:4), pp. 274-294.

Dess, G., and Beard, D. 1984, "Dimensions of Organizational Task Environments," *Administrative Science Quarterly* (29), pp. 52-73.

Dubosson-Torbay, M., A. Osterwalder, and Y. Pigneur. 2002, "E-business Model Design, Classification, and Measurements," *Thunderbird International Business Review* (44:1), pp. 5-23.

Eriksson, H., and M. Penker. 2000, "Business Modeling with UML," *Business Patterns at Work*, John Wiley & Sons, New York, USA.

Gartner. 2014, http://www.gartner.com/newsroom/id/2848718.

Gobble, M. M. 2013, "Big Data: The Next Big Thing in Innovation," *Research-Technology Management* (56:1), pp. 64.

Goes, P. B. 2014, "Editor's Comments: Big Data and IS Research," *MIS Quarterly* (38:3), pp. iii-viii.

Greene, William H. 2011. *Econometric Analysis*, 7th edition. Upper Saddle River, NJ: Prentice-Hall.

Grossman, R. L., and K. P. Siegel. 2014, "Organizational Models for Big Data and Analytics," Journal of Organization Design (3:1), pp. 20-25.

Hamel, G. 2002. *Leading the Revolution: How to Thrive in Turbulent Times by Making Innovation a Way of Life*, Harvard Business School Press Boston.

Hand, J. R. 2007, "Determinants of the Round-to-Round Returns to Pre-IPO Venture Capital Investments in US Biotechnology Companies," *Journal of Business Venturing* (22:1), pp. 1-28.

Hedman, J., and T. Kalling. 2003, "The business model concept: theoretical underpinnings and empirical illustrations," *European Journal of Information Systems* (12:1), pp. 49-59.

Hite, J. M., and W. S. Hesterly. 2001, "The Evolution of Firm Networks: From Emergence to Early Growth of the Firm," *Strategic Management Journal* (22:3), pp. 275-286.

Jacobs, A. 2009, "The Pathologies of Big Data," *Communications of the ACM* (52:8), pp. 36-44.

Jagadish, H., J. Gehrke, A. Labrinidis, Y. Papakonstantinou, J. M. Patel, R. Ramakrishnan, and C. Shahabi. 2014, "Big Data and its Technical Challenges," *Communications of the ACM* (57:7), pp. 86-94.

Keats, B. W., and Hitt, M. A. 1988, "A Causal Model of Linkages among Environmental Dimensions, Macro Organizational Characteristics, and Performance," *Academy of Management Journal* (31:3), pp. 570-598.

Klueber, R. 2000, "Business Model Design and Implementation for services," In *Proceedings of Americas Conference on Information Systems*, Long Beach, CA, 2000.

Kumar, A., F. Niu, and C. Ré. 2013, "Hazy: Making it Easier to Build and Maintain Big-Data Analytics," *Communications of the ACM* (56:3), pp. 40-49.

LaValle, S., E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz. 2013, "Big Data, Analytics and the Path from Insights to Value," *MIT Sloan Management Review* (52), pp. 20-32.

Lazer, D., R. Kennedy, G. King, and A. Vespignani. 2014, "The Parable of Google Flu: Traps in Big Data Analysis," *Science* (343:14 March).

Lee, Y., S. Madnick, R. Wang, F. Wang, and H. Zhang. 2014, "A Cubic Framework for the Chief Data Officer: Succeeding in a World of Big Data," *MIS Quarterly Executive* (13:1), pp. 1-13.

Lin, M., X. Ke, and A. B. Whinston. 2012, "Vertical Differentiation and a Comparison of Online Advertising Models," *Journal of Management Information Systems* (29:1), pp. 195-236.

Liu, C. Z., Y. A. Au, and H. S. Choi. 2014, "Effects of Freemium Strategy in the Mobile App Market: An Empirical Study of Google Play," *Journal of Management Information Systems* (31:3), pp. 326-354.

McAfee, A., and E. Brynjolfsson. 2012, "Big Data: The Management Revolution," *Harvard Business Review* (90:10), Oct, pp. 60-6, 68, 128.

Magretta, J. 2002, "Why Business Models Matter," *Harvard Business School Publishing Corporation*.

Markides, C., and C. D. Charitou. 2004, "Competing with Dual Business Models: A Contingency Approach," *The Academy of Management Executive* (18:3), pp. 22-36.

Miller, D., and Friesen, P. 1980, "Archetypes of Organizational Transition," *Administrative Science Quarterly* (25:2), pp. 268-299.

Newkirk, H. E., and A. L. Lederer. 2006, "The Effectiveness of Strategic Information Systems Planning Under Environmental Uncertainty," *Information & Management* (43:4), pp. 481-501.

Niculescu, M. F., and D. Wu. 2014, "Economics of Free Under Perpetual Licensing: Implications for the Software Industry," *Information Systems Research* (25:1), pp. 173-199.

Normandeau, K. 2013, "Beyond Volume, Variety and Velocity is the Issue of Big Data Veracity," *Inside Big Data*.

Obermiller, C., and E. R. Spangenberg. 1998, "Development of a Scale to Measure Consumer Skepticism toward Advertising," *Journal of Consumer Psychology* (7:2), pp. 159-186.

OIG. 2005, "Implementation of E-Government Principles," https://www.fdicig.gov/reports05/05-018-508.shtml.

Osterwalder, A., Y. Pigneur, and C. L. Tucci. 2005, "Clarifying Business Models: Origins, Present, and Future of the Concept," *Communications of the Association for Information Systems* (16:1), pp. 1.

Pateli, A. G., and G. M. Giaglis. 2004, "A Research Framework for Analysing eBusiness Models," *European Journal of Information Systems* (13:4), pp. 302-314.

Pavlou, P. A., and O. A. El Sawy. 2006, "From IT Leveraging Competence to Competitive Advantage in Turbulent Environments: The Case of New Product Development," *Information Systems Research* (17:3), pp. 198-227.

Petrovic, O., C. Kittl, and R. D. Teksten. 2001, "Developing Business Models for Ebusiness," *Available at SSRN 1658505*.

Pfeffer, J., and Salancik, G. 1978. The External Control of Organizations: A Resource Dependence Perspective, Harper and Row, New York.

Pouloudi, A., K. Vassilopoulou, and X. Ziouvelou. 2003, "A societal perspective on E-Business adoption," *Journal of Information, Communication and Ethics in Society* (1:3), pp. 149-165.

Rai, A., and X. Tang. 2013, "Research Commentary-Information Technology-Enabled Business Models: A Conceptual Framework and a Coevolution Perspective for Future Research," *Information Systems Research* (25:1), pp. 1-14.

Sabherwal, R., and S. Sabherwal. 2007, "How do Knowledge Management Announcements Affect Firm Value? A Study of Firms Pursuing Different Business Strategies," *Engineering Management, IEEE Transactions on* (54:3), pp. 409-422.

Susarla, A., A. Barua, and A. B. Whinston. 2009, "A Transaction Cost Perspective of the" Software as a Service" Business Model," *Journal of Management Information Systems* (26:2), pp. 205-240.

Tambe, P. 2014, "Big Data Investment, Skills, and Firm Value," *Management Science* (60:6), pp. 1452-1469.

VanderMeer, D., K. Dutta, and A. Datta. 2012, "A Cost-Based Database Request Distribution Technique for Online E-Commerce Applications," *MIS Quarterly* (36:2), pp. 479-507.

Vassilopoulou K., X. Ziouvelou, A. Pateli, and N. Pouloudi. 2003 "Examining e-Business models: Applying a Holistic Approach in the Mobile Environment," In *Proceedings of 11th European Conference on Information Systems (ECIS)* - Naples, June 16-21, 2003.

Venkatraman, N., and J. E. Prescott. 1990, "Environment-strategy Coalignment: An Empirical Test of its Performance Implications," *Strategic Management Journal* (11:1), pp. 1-23.

Wade, M., and J. Hulland. 2004, "Review: The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research," *MIS Quarterly* (28:1), pp. 107-142.

Weill, P., and M. Vitale. 2002, "What IT Infrastructure Capabilities are Needed to Implement e-Business Models," *MIS Quarterly Executive* (1:1), pp. 17-34.

Xu, S. X., and X. M. Zhang. 2013, "Impact of Wikipedia on Market Information Environment: Evidence on Management Disclosure and Investor Reaction," *MIS Quarterly* (37:4), pp. 1043-1068.

Xue, L., G. Ray, and B. Gu. 2011, "Environmental Uncertainty and IT Infrastructure Governance: A Curvilinear Relationship," *Information Systems Research* (22:2), pp. 389-399.

Yayla, A. A., and Hu, Q. 2012, “The Impact of IT-Business Strategic Alignment on Firm Performance in a Developing Country Setting: Exploring Moderating Roles of Environmental Uncertainty and Strategic Orientation,” *European Journal of Information Systems* (21:4), pp. 373-387.

Zott, C., and R. Amit. 2007, "Business Model Design and the Performance of Entrepreneurial Firms," *Organization Science* (18:2), pp. 181-199.

Zott, C., R. Amit, and L. Massa. 2011, "The Business Model: Recent Developments and Future Research," *Journal of Management* (37:4), pp. 1019-1042.

Tables of Chapter 2

Table 1- Descriptive Statistics

		Avg.	**Min**	**Max**	**S.D.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	CAR	0.31%	-17.42%	16.53%	5.82%							
2	Velocity (% in text)	0.21%	0.04%	0.38%	0.04%	0.21**						
3	Variety (% in text)	0.19%	0.03%	0.31%	0.05%	0.18*	0.09					
4	Volume (% in text)	0.26%	0.05%	0.42%	0.08%	0.23**	0.09*	0.08$^{\#}$				
5	Veracity (% in text)	0.15%	0.02%	0.29%	0.06%	0.27**	0.09$^{\#}$	0.06	0.08$^{\#}$			
6	Dynamism	1.26	0.32	0.05	2.08	-0.08	0.07$^{\#}$	0.02	0.05	0.06		
7	Complexity	0.31	0.22	0.03	0.74	-0.04	0.03	0.10*	0.04	0.02	0.10*	
8	Munificence	0.86	0.37	0.12	0.92	0.04	-0.07$^{\#}$	-0.09*	-0.11*	- 0.08$^{\#}$	-0.08	- 0.06

*$^{\#}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; N= 651.*

Table 2- CAR [-1, +1] - Equally Weighted

	Full Sample Analysis		Sub-Sample Analysis		
	Model 1	Model 2	Model 3	Model 4	Model 5
			Security	Infrastructure	Analytics
Investment Value (normalized by org sales)	0.326***	0.318***	0.306***	0.322***	0.332***
Firm Size (total assets)	0.082**	0.076***	0.079***	0.063**	0.059**
Time	0.012	0.011	0.009	-0.011*	0.014*
Velocity	0.036**	0.039**	0.036**	0.028**	0.018*
Variety	0.014*	0.018*	0.004	-0.003	0.054***
Volume	0.042**	0.051**	0.026**	0.049***	0.024**
Veracity	0.027*	0.022*	0.054***	0.008	0.042**
Analytics	0.018*	0.016*			
Security	0.031**	0.028**			
Analytics*Velocity		0.009			
Analytics*Variety		0.078***			
Analytics*Volume		-0.008			
Analytics*Veracity		0.064**			
Security*Velocity		0.011			
Security*Variety		0.002			
Security*Volume		-0.007			
Security*Veracity		0.081***			
N	*651*	*651*	*231*	*184*	*236*
Adjusted R^2 (%)	*12.4*	*13.6*	*11.3*	*11.7*	*12.8*
ΔR^2 *(%)*		*1.2****			

*Industry, year, acquired, and main dummies are included but the dummy coefficients are not reported for brevity; * p < 0.05, ** p < 0.01, *** p< 0.001; Robust standard errors are estimated by clustering errors around firm dummies. There is at least a 300-day distance between announcements of the same firm.*

Table 3- Robustness Analyses: Alternative Measures for Core Constructs

	CAR [-2, +2]- Equally Weighted			CAR [-1, +1]- Value Weighted			Alt. Measures of 4Vs Emphasis		
	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
	Security	Infra.	Analytics	Security	Infra.	Analytics	Security	Infra.	Analytics
Investment Value (normalized by org sales)	0.321***	0.313***	0.304***	0.284***	0.292***	0.318***	0.305***	0.344***	0.279***
Firm Size (total assets)	0.062***	0.051**	0.073**	0.077***	0.082***	0.062*	0.064***	0.076**	0.075**
Time	0.004	-0.013*	0.010*	-0.003	-0.011*	0.015*	-0.0043	-0.019*	0.013*
Velocity	0.029**	0.023**	0.023*	0.030*	0.032*	0.017*	0.022*	0.021*	0.025*
Variety	-0.007	0.005	0.062***	0.012	0.009	0.039*	-0.006	-0.008	0.016*
Volume	0.033**	0.066**	0.017*	0.042**	0.072***	0.041**	0.051**	0.064**	0.029*
Veracity	0.062***	0.013	0.031*	0.068***	-0.004	0.052***	0.074**	0.008	0.043**
N	*231*	*184*	*236*	*231*	*184*	*236*	*214*	*168*	*199*
Adjusted R^2 (%)	*12.1*	*11.4*	*11.2*	*10.1*	*10.6*	*11.7*	*11.2*	*13.7*	*9.6*

*Industry, year, acquired, and main dummies are included but the dummy coefficients are not reported for brevity; * p < 0.05, ** p < 0.01, *** p< 0.001; Robust standard errors are estimated by clustering errors around firm dummies. There is at least a 300-day distance between announcements of the same firm.*

Table 4- Full Models

	Direct	Interaction	[-2, +2]	Value-Weighted	Alt. Measures of 4Vs
DV= CAR	Model 15	Model 16	Model 17	Model 18	Model 19
Velocity	0.093**	0.082**	0.068**	0.073**	0.059*
Variety	0.082**	0.064**	0.086*	0.092***	0.041*
Volume	0.078**	0.053**	0.088**	0.067*	0.091**
Veracity	0.096**	0.032**	0.077*	0.082**	0.093*
Analytics	0.031*	0.026*	0.028*	0.031**	0.056*
Security	0.044*	0.037**	0.071	0.080*	0.029
Dynamism	0.133***	0.112***	0.159***	0.121**	0.134***
Complexity	0.102*	0.093**	0.084**	0.058*	0.091***
Munificence	-0.070*	-0.067*	-0.021	-0.029$^{\#}$	0.042**
Analytics*Velocity	0.005	0.002	0.003	-0.001	0.008
Analytics*Variety	0.048**	0.053*	0.039*	0.044**	0.052*
Analytics*Volume	0.011	0.009	0.003	0.000	0.002
Analytics*Veracity	0.073*	0.089***	0.071*	0.066**	0.069*
Security*Velocity	0.003	0.012	0.009	0.011	0.010
Security*Variety	0.008	0.010	0.005	0.002	0.002
Security*Volume	0.001	0.002	-0.006	0.003	0.006
Security*Veracity	0.088**	0.094*	0.102***	0.038$^{\#}$	0.057*
Dynamism * Velocity		0.173***	0.184***	0.122***	0.083**
Dynamism * Variety		0.018	0.010	0.009	0.004
Dynamism * Volume		0.009	0.011	0.012	0.005
Dynamism * Veracity		0.011	0.004	0.004	-0.006
Complexity * Velocity		0.013	0.012	0.007	0.003
Complexity * Variety		0.125***	0.092***	0.111***	0.098***
Complexity * Volume		0.018	0.012	0.014	0.009
Complexity * Veracity		0.093**	0.172***	0.048*	0.069**
Munificence * Velocity		-0.065*	-0.070*	-0.057**	-0.061*
Munificence * Variety		-0.082**	-0.088**	-0.091*	-0.073**
Munificence * Volume		-0.116***	-0.131***	-0.109**	-0.094**
Munificence * Veracity		-0.049*	-0.081*	-0.042*	-0.033*
N	651	651	651	651	651
Adjusted R^2 (%)	13.6	16.3	18.2	16.8	15.8
ΔR^2 (%)		2.7***			

*Industry, year, acquired, and main dummies are included but the dummy coefficients are not reported for brevity; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Robust standard errors are estimated by clustering errors around firm dummies. There is at least a 300-day distance between announcements of the same firm.*

Table 5- Payoffs for the BDV

	Full Sample	Security	Analytics	Computing
	Model 20	Model 21	Model 22	Model 23
DV= Raised Capital				
Velocity	0.115***	0.152***	0.119***	0.128***
Variety	0.183**	0.032	0.203***	0.027
Volume	0.064**	0.078**	0.033*	0.068*
Veracity	0.218***	0.321***	0.256***	0.012
Analytics	0.022*			
Security	0.038*			
Number of employees	0.052*	0.063**	0.049*	0.081*
Education of co-founders	0.093**	0.231**	0.117**	0.198***
Years established	-0.011	-0.009	-0.012	-0.01
Funding round count	0.116***	0.125***	0.142***	0.133***
Acquired	0.204***	0.354***	0.242***	0.198***
B2B	0.005	0.007	-0.004	0.003
N	2026	714	868	444
Adjusted R^2 (%)	0.19	0.24	0.21	0.18

Coefficients of dummies representing the secondary scope of the BDV, location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$;
Robust standard errors are estimated by clustering errors around start-up dummies.

Table 6- Importance of Big Data Emphasis in Different Scopes

	Velocity	Variety	Volume	Veracity
Security	✓	✗	✓	✓
Infrastructure	✓	✗	✓	✗
Analytics	✓	✓	✓	✓

Appendix A. Examples of Announcements about Investments in BDVs

Reported by Techcrunch, June 10, 2013:

Walmart, via its Silicon Valley innovation lab @WalmartLabs, has made another acquisition today, continuing its shopping spree. The company is announcing that predictive intelligence startup Inkiru will be joining Walmart Labs to accelerate the retail giant's analytics capabilities. Financial terms of the deal were not disclosed.

Inkiru's platform is an active learning system that combines predictive intelligence, data analytics and a decision engine to influence and determine customer interactions. Benefits to using Inkiru include being able to reduce fraud, improve customer segmentation and targeting, and more.

In a post announcing the acquisition, Walmart Labs writes that Inkiru's predictive analytics platform will add data analysis capabilities, including site personalization, search, fraud prevention and marketing. From the post: "Walmart's data scientists will now be able to work with big data directly and create impact faster than ever before."

Walmart Labs is known for being acquisitive when it comes to snapping up early-stage startups to test new ideas in e-commerce. Some of these startups eventually get folded into the company's e-commerce site and other online operations.

It looks like we can expect Walmart.com to improve personalization, which isn't too surprising. Data analytics and personalization are certainly two areas where retailers are doubling down as a way to both add to the customer experience and draw more conversions online.

Reported by marketwatch.com, June 27, 2013:

Raytheon Company has acquired a privately held company, Visual Analytics Incorporated, further extending Raytheon's capabilities to meet the data analytics, data visualization and information sharing needs of its customers. Terms of the transaction were not disclosed.

As one of the largest processors of data for the intelligence community, Raytheon has extensive experience handling large data sets and providing actionable information to its customers. The acquisition of Visual Analytics will add advanced analytic products and knowledge management solutions with intuitive user interfaces to Raytheon's offerings to its customers. It will also broaden the company's customer base in federal, state and local law enforcement.

"The addition of Visual Analytics will further strengthen Raytheon's capabilities in the area of data analytics," said Lynn Dugle, president of Raytheon's Intelligence, Information and Services (IIS) business. "This will allow us to bring new, innovative visualization offerings to our customers as they address the continuous challenge of increasing analyst efficiency and effectiveness while transforming data into actionable intelligence."

Appendix B. Additional Analysis with Different Sets of Bi-grams pertaining to Emphasis on 4Vs

DV= CAR	Frequency of 4V Keywords -5% Model B1	Frequency of 4V Keywords -20% Model B2	4Vs calculated with problematic bi-grams dropped Model B3
Velocity	0.068*	0.029*	0.088*
Variety	0.107**	0.072**	0.042**
Volume	0.072**	0.046#	0.033#
Veracity	0.049*	0.070**	0.021*
Analytics	0.013	0.021	0.004
Security	0.020	0.004	0.008
Dynamism	0.072*	0.099**	0.072*
Complexity	0.042*	0.028*	0.018#
Munificence	-0.012	0.013#	0.010
Analytics*Velocity	-0.002	0.002	0.001
Analytics*Variety	0.082***	0.023*	0.091***
Analytics*Volume	0.060	0.002	0.005
Analytics*Veracity	0.092*	0.043#	0.053**
Security*Velocity	0.007	0.000	0.011
Security*Variety	0.000	-0.004	-0.016
Security*Volume	0.008	0.001	0.003
Security*Veracity	0.038#	0.022#	0.041*
Dynamism * Velocity	0.201**	0.117***	0.092*
Dynamism * Variety	0.003	0.001	0.003
Dynamism * Volume	0.005	0.017	-0.009
Dynamism * Veracity	-0.001	-0.004	0.010
Complexity * Velocity	-0.010	0.000	0.018
Complexity * Variety	0.052*	0.105*	0.088**
Complexity * Volume	0.002	0.003	0.005
Complexity * Veracity	0.051*	0.023*	0.112***
Munificence * Velocity	-0.063*	-0.028#	-0.033*
Munificence * Variety	-0.111***	-0.061*	-0.018#
Munificence * Volume	-0.028#	-0.032*	-0.029#
Munificence * Veracity	-0.033#	-0.081**	-0.073**
N	651	651	651
Adjusted R^2 *(%)*	15.8	14.6	14.2

*Industry, year, acquired, and main dummies are included but the dummy coefficients are not reported for brevity; * p < 0.05, ** p < 0.01, *** p< 0.001; Robust standard errors are estimated by clustering errors around firm dummies. There is at least a 300-day distance between announcements of the same firm.*

Chapter 3:
Socially-Constructed Innovations in New IT Ventures

Abstract

The network view is a prevalent theoretical lens to describe the success of new ventures. Nonetheless, the relevant literature faces a number of shortcomings. First, while embeddedness in networks providing access to *financial capital* resources has been studied, the structure of networks facilitating access to *intellectual capital* is less understood. Therefore, this paper's first goal is to understand the role that intellectual capital networks play, along with the financial capital networks, to make new ventures successful. Second, most studies investigating the role of network embeddedness in new ventures have mainly focused on either one type of network tie or have aggregated different types of network ties to understand the role of network position. However, different types of network ties may shape network structures that are distinct, and therefore, their aggregation may mask important information about their value to a new venture. Thus, the paper's second goal is to study different types of network ties, in both financial capital and intellectual capital networks, and understand how these different networks interact to make new ventures successful. Focusing on Big Data Ventures (BDVs), as ventures active in an industry where innovation is socially-constructed, we investigate the structure of personal and investment networks, as networks facilitating access to financial capital, and educational and professional networks, as networks facilitating access to intellectual capital. We also differentiate between ventures that pursue radical versus incremental innovations and hypothesize about the difference in network positions ideal for each type of innovation.

Results of our study on 2,009 BDVs observed between 2011 and 2014 show that: a) educational and professional networks have distinct structures, and thus, treating them as separate networks is more informative; b) the structure of personal and investment networks calls for super-imposing them; c) achieving a desirable mix of structural holes and density for venture pursuing radical innovations is possible when those structural traits occur in different networks (i.e., high network density in education network, and high level of structural holes in the professional network or vice versa); and d) eigenvector centrality in the superimposed financial capital network is positively associated with higher levels of raised capital for new ventures. Moreover, our post-hoc matched sample analysis reveals that unlike in the Big Data industry, ventures in the Medical Devices industry do not exhibit the same benefits from embeddedness in the inter-venture intellectual capital networks. We discuss how this empirical evidence hints at the distinct *socially-constructed* nature of IT innovations.

Keywords:*embeddedness, big data venture, financial capital network, intellectual capital network, socially-constructed innovation, structural holes, network density, eigenvector centrality.*

Introduction

The network view is a prevalent theoretical lens to describe the success of new ventures (Brüderl and Preisendörfer 1996, Baum et al. 2000, Florin et al. 2003, Maurer and Eber 2006; Evers and O'Gorman 2011; Zanre and DeCarolis 2016). This lens assumes a positive relation between the networking activities of a founder and its venture's success. The rationale behind this expectation is the theory of socially embedded ties, according to which socially embedded ties allow entrepreneurs to: a) obtain resources cheaper than they could be obtained through markets; and b) secure resources that would not be available in markets at all (e.g. reputation, customer contacts; Witt 2004). The extant research on the role of networks in the success of new ventures has mostly focused on the strength and weakness of founders' *personal* ties (e.g., Brüderl and Preisendörfer 1996, Jenssen and Greve 2002, Florin et al. 2003) and their effect on financial performance of new ventures (e.g., Baum et al. 2000, Lechner et al. 2006).

Nonetheless, the current literature[14] faces a number of shortcomings. First, focusing on the late-stage performance of new ventures, prior studies overlook the effect of network structure on the initial phases of forming new ventures. Focusing on the late stages of venture development, the existing literature has emphasized *financial capital networks*, i.e., networks where ties among the members are established through direct social interaction, as means to access resources, mainly financial and reputational, required to enter a market and survive (e.g., Elfring and Hulsink 2003). However, the early phases of venture development are also important because they involve *creation* and *refinement* of the venture's innovation (Florin et al. 2003). This is in contrast with late stages of venture's development, where *appropriating* market share, competing, and survival are the main tasks. In the early stages, in addition to depending on their

[14] See Appendix A for a brief summary of notable literature about the network view and success of new ventures.

social networks to obtain financial and reputational resources to kick-start their business, BDVs depend on their *intellectualnetworks* (i.e., networks where ties among the members are established through knowledge-related associations) to develop their innovation. Specifically, new ventures develop products/services on a spectrum of innovativeness (incremental to radical). Previous literature suggests that network structures required for success of each type of innovation are distinct (Elfring and Hulsink 2003). Therefore, the first objective of this study is to extend the existing literature by considering the role that intellectual networks play, in addition to the role of social networks, in the success of new ventures generally and BDVs specifically. Also, we intend to study this role relevant to the type of a new venture's innovation (radical vs. incremental). Figure 1 depicts how this study departs from the existing literature's focus on the late stages of venture development and thereby includes access to intellectual networks in the discussion about network factors affecting the success of new ventures.

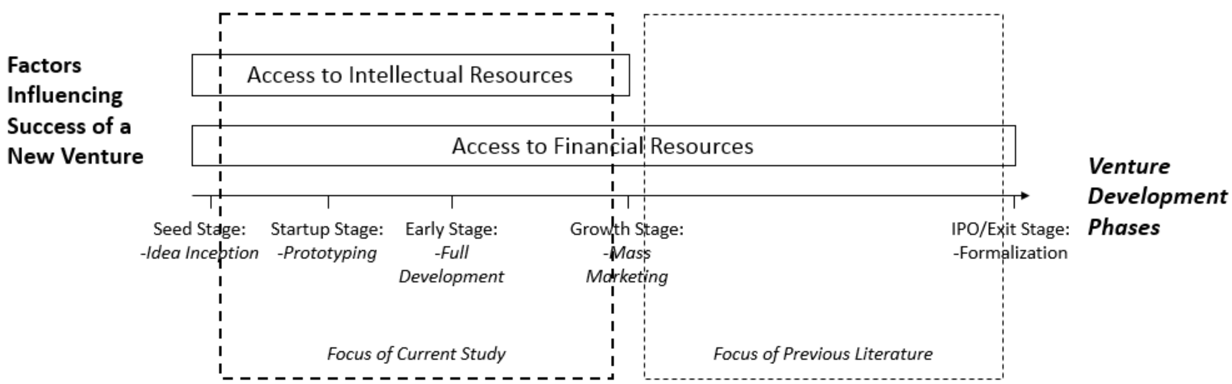


Figure 1. Comparison of the Developmental Focus of this Essay and the Previous Literature

Second, the current literature has mainly focused on either one type of founders' network (e.g., Baum et al. 2000, Jenssen and Greve 2002, Jenssen and Koeing 2002, Maurer and Eber 2006) or has aggregated different types of founders' networks (e.g., Florin et al. 2003) to study the role of network structure in the success of new ventures. However, venture founders are embedded in different types of networks (Lechner et al. 2006). Friendship ties, educational ties, and professional ties are among different types of network ties that a venture founder can have with relevant individuals in his/her environment. Lechner and colleagues (2006) suggest and empirically show that the same position in different types of networks results in different outcomes and encourages researchers to consider separately studying networks of distinct nature. Building on Lechner et al.'s work, the second objective of this paper is to study different network types in which a BDV is embedded and understand the effect of these networks' structure on the success of the BDV.

To investigate the role of *intellectual capital networks*, we consider a BDV's educational and professional ties with other BDVs. The general literature on entrepreneurial innovations (e.g., Robinson and Sexton 1994; Van Praag et al. 2013), as well as the literature on development of IT innovations (e.g., Couger 1973; Kautz et al. 2007), suggests that innovators access technical knowledge through two main sources: formal education and professional experience. While formal education provides innovators with basic technical knowledge, professional experience provides access to tacit technical knowledge or organizational proprietary knowledge that is not presented in formal curricula taught in colleges and universities. Individuals with similar educational and professional background share a common language (e.g., Preston and Karahanna 2009) that facilitates transfer of cutting-edge, and often complex, knowledge that is usually required in the development of technological innovations (e.g., Kuemmerle 2003). While some BDVs pursue the development of a radical innovation, others might pursue the development of a more incremental one. First, we discuss how intellectual networks affect a BDV's radical or incremental orientation in the early phases of venture development. Then, we discuss the role that intellectual networks play in the development of a venture's initial idea, radical or incremental, and raising the capital needed to expand the business.

To investigate the role of *financial capital networks*, we consider a BDV's personal and investment ties with other BDVs, as well as with investors such as angels and venture capitalists. We define personal networks as networks with ties constructed based on non-financial social interactions that can include emotional and public encouragement for the BDV. Previous literature has documented positive financial gains from similar ties, including kinship, friendship, and family ties (e.g., Brüderl and Preisendörfer 1996); therefore, we consider personal ties a major channel for accessing reputational and financial resources. Also, we consider investment networks which are networks with ties to previous investors. Ties to previous investors, including angels or venture capitalists, can allow a BDV to access unexploited financial resources. Both personal and investment networks can provide a BDV with reputational and financial resources it needs to raise capital.

Building on structural theories of innovation and the theory of social embeddedness, this paper proposes to focus on structural holes and density in intellectual networks of a BDV, while considering eigenvector centrality[15] in its social networks as the key determinant of success, i.e., raised capital. The developed hypotheses are tested using objective data from AngelList.com, focusing on 2,009 BDVs active from 2011 to 2014. The results show that: a) educational and professional networks have distinct structures, and thereby treating them as separate networks is more informative; b) the structure of personal and investment networks call for super-imposing them, considering personal and investment ties simultaneously; and c) achieving a desirable mix

[15]Eigenvector centrality is a special measure of centrality that considers the importance ties, in addition to the number of ties, when identifying the extent of an ego's centrality in a given network.

of structural holes and density for radical innovations is possible when those structural traits occur in different networks (i.e., high network density in education network, and high level of structural holes in the professional network or vice versa).

Innovation and New Ventures

Innovation is at the heart of entrepreneurial firms at the early stages of development (Zott and Amit 2007). Absent traditional firm resources, such as liquidity, reputation, and extensive human capital, innovation is the main source of value-creation for these ventures (Zott and Amit 2007). To develop, grow, and stabilize, new ventures need to attract capital from venture capitalists and angels, mainly through a persuasive innovation that shows the potential for success (Timmons and Bygrave 1986). New ventures follow different strategies in developing innovations. Some focus on radical novelty, where product/service is a clear often a risky departure from the existing technology (Ettlie et al. 1984). Others pursue incremental innovations where the focus is on improvements, modifications, or re-configuration of the existing technology (Ettlie et al. 1984). While both types of innovation are shown to influence performance of new ventures positively (Rosenbusch et al. 2011), different structures are required to support and nourish them (Ettlie et al. 1984; Elfring and Hulsink 2003). Below, utilizing a networks lens, we explain the structural features that support radical and incremental innovations.

Theoretical Development

A new venture's ability to raise capital depends on two conditions. First, new ventures should have access to channels that enable them present their work to capitalists and attract them (e.g., Ferray 2003). Second, the innovation offered by the venture should be deemed lucrative for the accessed investors. In doing so, the quality of innovation and its development play a key role in convincing a capitalist to invest (e.g., McMillan et al. 1985; Kollman and Kuckertz 2010). From a networks perspective, satisfying the two conditions requires access to different types of networks and different structural positions. Specifically, we label networks allowing access to capitalists'***financial capital networks***, and label networks that enable creation, refinement, and development of an innovation ***intellectual capital networks***. Below, we discuss the network theories relevant to each condition.

Theories of Social Embeddedness and Access to Financial Capital

Theories of embeddedness suggest that entrepreneurs become more successful as they become more embedded in social ties with others because social ties facilitate accessing resources and information in a fast and economically-efficient fashion (Uzzi 1997). Socially embedded ties allow entrepreneurs know, approach, and persuade individuals and firms that seek investment opportunities. Reach and access are not the only feature of socially-embedded ties. Rather, social ties create a degree of network reputation (Uzzi 1997; Uzzi 1999) that is essential for the flow of capital to new ventures. Ties to influential entities enhance a venture's worth in the eyes of others, leading to an enhanced reputation. The existing research suggests that new ventures are viewed as uncertain investments (Kollman and Kuckertz 2010). The reputation stemming from a strong network position facilitates trust (Gluckler and Armbruster 2003), a key element in financial decisions especially when an investment carries high levels of uncertainty (Bhide and Stevenson 1992). Therefore, socially-embedded ties enable accessing investors under a level of trust that is pertinent for suppressing the threat of newness investors face when considering an investment in a new venture.

From a structural perspective, size and centrality are discussed as structural attributes that pertain to the *access* and *reach* to entrepreneurial financial resources (Hoang and Antonic 2003).

Specifically, the size of a founder's ego network has been primarily discussed and empirically investigated (e.g., Aldrich and Reese 1993; Hansen 1995). Centrality is conceptually similar to network size. While network size determines the extent to which resources are available, centrality "explicitly includes the ability to access (or control) resources through indirect as well as direct links" (Hoang and Antonic 2003, p. 171). The existing research has characterized a new venture's access to financial resources through considering the network centrality of its founder(s) (e.g., Brajkovich 1994; Johannisson et al. 1994; Powell et al. 1996).

In spite of research supporting the role that central positions play in accessing resources, plain degree measures of centrality fail to reflect the reputation and therefore the trust that network ties carry. As it was noted earlier, access to trusted ties is needed for the flow of capital to new ventures. Therefore, new ventures with the same number of social ties may be different in terms of their access to *trusting* resources, depending on the reputation of those they are connected to. The current literature on social network structures suggests that to account for the reputation carried by social ties, the centrality of edges needs to be considered. This is based on the theory that ties to more influential actors bear more reputation (Hanneman and Riddle 2005). Consistent with this theory, the concept of eigenvector centralityis introduced (Bonacich 1972) and utilized in cases where reputation, in addition to the access to resources, is considered (e.g., Mehra et al. 2006). Similarly, we build on the notion of eigenvector centrality to argue about the network structures that facilitate a BDV's access to trusting investors.

New ventures become embedded in financial ties by establishing two types of connections. The first type is connections with other ventures and investors through ***personal ties***. These personal ties can exist due to social interactions such as friendship among founders and employees and followership (in case of online communities) (e.g., Lechner et al. 2006). Second,

investment ties, i.e., ties with previous investors,can facilitate financial embeddedness. The two types of ties are different in terms of content. In the former, social interactions are the basis for connection, whereas in the latter, financial transactions play a key role. We suggest that eigenvector centrality in financial capital networks (consisted of personal and investment ties) increases access to trusting investors.

Personal ties with more central investors increase the reach and reputation for a new venture. On the one hand, more ties with capitalists increase the level of access to them. On the other hand, personal ties with popular and influential investors signal dependability of a venture and thereby attract other investors. In addition to ties with potential investors, personal ties to other (central) ventures can also increase access to more resources. Through ties to other ventures, a venture can extend its access to those ventures' investors. Moreover, personal ties to highly central ventures signal dependability and trustworthiness. Influential ventures are likely to be successful in raising capital and showing potential. For newly emerged ventures or those at the early stages of development, with the threat of newness glooming (Chen et al. 2009), ties to successful and influential ventures can also boost reputation. This can be explained by *social homophily*, a well-documented phenomenon that suggests personal ties often emerge between social actors with similar traits and qualities (McPherson et al. 2001). For potential investors, an influential venture's tie to a new venture can signal that the founders of the new venture, although less known, share the same talent and experience as the in-tie influential venture.

In addition to personal ties, investment ties can also enhance a new venture's reach and reputation. First, investors from the past rounds of investment are very likely to invest in the next rounds due to the sunk costs of their initial investment (Hallen and Eisenhardt 2012). Moreover, the threat of newness is less salient for previous investors as they have already spent some time to research the venture in the previous round(s) of investment. The ongoing monitoring of a business venture and observing its survival to another round of capital raising can reduce perceived risks for an investor. Second, the empirical evidence suggests that new investors rely on referrals by previous investors (Hallen and Eisenhardt 2012). Specifically, the more central and influential investors have higher levels of network reach and hence are more likely to be able to introduce a new venture to their ties. Moreover, a previous investment by an influential investor signals the new venture's dependability to the potential investors. Highly central investors, i.e., those with a large number of investments, have more financial capabilities. Research suggests that well-endowed capitalists invest in better ventures (Hsu 2004; Sørensen 2007; Knill 2009). Therefore, new investors perceive a venture with ties to central investors as a business with more potentials and/or less risks. Hence, we hypothesize that:

> H1: Higher eigenvector centrality in the financial capital network, consisting of personal and investment ties, is associated with higher capital raised by a BDV in round t.

Big Data Innovations and Intellectual Capital Networks

The existing literature suggests that "when the knowledge base of an industry is both complex and expanding and the sources of expertise are widely dispersed, the locus of innovation will be found in networks of learning, rather than in individual firm" (Powell et al. 1996, p. 116). Big Data fits the description of such an industry. First, the existing literature describes Big Data innovations as complex and relying on multiple disciplines of science (e.g., Chen et al. 2012; Dhar 2013). Further, Big Data is described as a growing and expanding area (Goes 2014). Therefore, development, refinement, and advancement of Big Data innovations are *socially-constructed* in intellectual networks, rather than being confined to individual firms. In addition to the general literature on management of innovations (e.g., Gilbert et al. 2008), the existing literature on IT innovations provides empirical evidence suggesting learning about innovations happens in a social discourse in the IT context (Wang and Ramiller 2009). Therefore, a BDV's success in the development of a lucrative innovation highly depends on its structural position in the intellectual network around it. In the section below, we introduce structural theories of innovation and discuss structural positions that help a BDV with incremental and radical innovations grow.

Two closely related but distinct streams of social networks research have theorized about the intellectual capital embedded in networks and discussed the ways through which innovation development is enabled. First, the literature on structural holes (Burt 2004) suggests that the presence of structural holes facilitates access to a diverse set of resources, increasing the possibility to innovate. When two separate clusters possess non-redundant information, there is said to be a structural hole between them (Burt 2009). The theories of structural holes build on the notion that in the context of networks, intellectual capital exists where people have an advantage because of their location in a network. Contacts in a network provide information, opportunities, and perspectives that can be beneficial to the central player in the network. These theories emphasize that most social structures tend to be characterized by dense clusters of strong connections (Burt 2004) and that information within these clusters tends to be rather homogeneous and redundant. However, it is contended that non-redundant information is usually obtained through contacts in different clusters, a case that happens when structural holes exist. Thus, networks rich in structural holes have a form of intellectual capital by offering information benefits. The player in a network that bridges structural holes is able to access information from diverse sources and clusters (Burt 2009). For new ventures, the presence of structural holes enables accessing to more diverse information and increases the likelihood of innovation inception, and at the later stages, innovation refinement.

Second, the theory of weak ties (Granovetter 1973) has been utilized to shed more light on the phenomenon by explaining the effects of network structure on development of innovations. Tenets of this theory suggest that that different network positions, i.e., rich in cohesion or structural holes, enable differing tie strengths such that individuals embedded in networks rich with structural holes, due to their access to non-redundant resources and the broader reach of their network, establish weaker ties that are more proper to acquire diverse knowledge (Hansen 1999). On the contrary, more cohesive networks, characterized by the existence of more ties among the network actor, enable stronger ties that enable transfer of rich knowledge, often enabling more drastic innovations (Hansen 1999).

Although the general role of strong and weak ties, as well as structural holes and network cohesion, are realized in the existing literature, there is disagreement regarding the role that each type of network characteristics plays the success of entrepreneurial firms (Johannisson 2000; Hite and Hesterly 2001; Rowley et al. 2000). Specifically, the role of network characteristics in the early stages of a venture's development has been less clear (Bloodgood et al. 1995; Steier and Greenwood 2000). The existing literature suggests conflicting findings. For example, in some instances "both strong and weak ties are argued to be positively related to performance" (Rowley et al., 2000, p. 369) and in other cases, strong ties, enabled by highly dense networks, are deemed detrimental to development of ideas (Gargiulo andBenassi, 1999). Burt (2000) argues that the two types of ties, strong and weak, play different and distinct role in enabling innovation. On one hand, dense networks and the resulting strong ties are regarded as means to facilitate exchange of rich information, and complex and tacit knowledge (Krackhardt 1992; Starr and MacMillan 1993; Rowley et al. 2000). On the other hand, structural holes and their enablement of weak ties are beneficial as they facilitate access to diverse information

(Granovetter 1973, 1982; Burt 1992). Works by Uzzi (1996, 1997), Hite and Hesterly (2001), and Rowley et al. (2000) indicate that a mix of structural holes and dense ties can explain the network benefits for new ventures.

A contingency approach is often utilized to understand the mix in which structural holes and network density operate create success for entrepreneurial firms. For instance, the stage of development in which a venture is has been noted as a contingency factor such that in early stages there is a greater need for higher cohesion, whereas in the later stages of development, structural holes are more beneficial (Birley 1985; Bloodgood et al. 1995; Hite and Hesterly 2001). A second contingency factor in explaining the mix of structural holes and network cohesion is the industrial context. Specifically, structural holes are shown to be more instrumental in dynamic environments, whereas in stable environments, network density becomes more beneficial (Rowley et al. 2000). A third contingency has been the type of innovation, radical or incremental. While Elfring and Hulsink (2003) point to more agreed-upon role by structural holes as the provider of information diversity for new ventures, they offer a lens to understand the role that network density and strong ties play. Specifically, Elfring and Hulsink (2003, p. 414) describe the role of network density and strong ties as following: "Another strong tie advantage is related to the ability to exchange tacit knowledge. This mechanism may be particularly important to start-ups realizing more radical innovations. They are confronted with a new combination of resources from various backgrounds. The deployment of these complementary assets requires the exchange of tacit knowledge."

Overall, the theoretical arguments point to importance of structural holes for advancement of incremental innovations. Incremental innovations happen through the combination of existing innovations or by re-configuring them (e.g., Obstfeld 2005). Structural holes provide access to a diverse set of knowledge and thereby facilitate the development of incremental innovations. In addition to the theoretical arguments supporting the role of structural holes in development of incremental innovations, empirical findings suggest that for ventures pursuing incremental innovations, those with weaker ties are more likely to discover opportunities than those with strong ties (Elfring and Hulsink 2003).

On the other hand, it is contended that for ventures pursuing radical innovations, those having a mix of strong and weak ties are more likely to discover opportunities than those that do not have such a mix (Elfring and Hulsink 2003). That happens because for advancement of radical innovations, a combination of diverse knowledge and exchange of complex tacit knowledge is required.While access to more than enough diversity in a network traps innovators in myopic states where breaking the status-quo is hard (Obstfeld 2005), presence of strong ties along with weak ties is more important for ventures pursuing radical innovations as strong ties enable exchange of complex tacit knowledge, which is key for radical innovations (Elfring and Hulsink 2003). A novel and breakthrough idea is not a combination of different ideas or a re-configuration of the existing ones. A diverse knowledge about existing innovations allows entrepreneurs to understand the current status of an innovative field and define, or adopt, a niche area. After this phase, a deep understanding of the often tacit and complex technological knowledge is required to develop and refine an idea that is novel (Elfring and Hulsink 2003). Creation of breakthrough innovations requires a great extent of tacit knowledge exchange as evidenced by Smith et al. (2005), and the existing literature (Reagans and McEvily 2003) suggest that strong ties enabled by higher levels of network cohesion enable the exchange of such tacit and complex knowledge. Table 1 summarizes the potentials of network structures with high levels of structural holes and network cohesion, and Table 2 summarizes the findings of the extant literature regarding the type of network structures enabling incremental and radical innovations.

---Insert Tables 1 and 2 here---

Building on the above-mentioned literature, hypothesizing about the direct effect of structural holes and network density in the intellectual capital networks, i.e., educational and professional networks, is rather straight-forward. For both radical and incremental innovations, access to structural holes in either network is beneficial as it increases access to diverse knowledge and ideas. On the other hand, the literature mentions the importance of network density for radical innovations but not of incremental ones. Network density facilitates transfer of complex knowledge that is key to advancement of radical innovations. Therefore, based on the prior literature, we expect network density in both educational and professional networks has a positive effect on the capital raised by BDVs pursuing radical innovations. Moreover, we expect an insignificant effect in the case of BDVs pursuing incremental innovations. Because these relationships have been theorized in the previous literature, we avoid hypothesizing about them in this essay. Instead, our focus is on the interactions of structural positions in educational and professional networks.

We believe the focus on the mentioned interactions advances the prior literature theorizing about network structures enabling innovation development. For example, while achieving low levels of network cohesion and high levels of structural holes is possible in a single network (in case of incremental innovations), a simultaneous access to the structural holes and network cohesion for BDVs with radical innovations is unlikely. As the network density increases, redundant ties among individuals start to emerge. Therefore, reaching high levels of structural holes and network density in the same network might not be feasible. However, the intellectual networks of entrepreneurs can extend beyond a singular structure. Specifically, an entrepreneur's intellectual network can be shaped around ties that are based on formal education and professional experience. If the two networks are structurally distinct, one network can supply entrepreneurs with high levels of structural holes, and the other can supply strong ties through high level of network density. Below, we explain how different combinations of structural positions in the two networks affect the capital raised by BDVs pursuing a radical or incremental innovation.

For radical innovations, access to diverse knowledge and ability to communicate complex information are required for success. A possible way to access both is when in one network (e.g., educational), structural holes are present, and the other (e.g., professional) is a network with high density. Specifically, we suggest that high network density in the other network complements the diverse access to the community knowledge. Therefore, as the network density increases in one network, the BDV is able to make better use of its diverse access to knowledge through high structural holes in the other. High network density in one network allows breakthrough ideas to emerge through exchange of complex knowledge, building on the diverse knowledge obtained through structural holes of another network. Therefore:

> H2: For radical innovations, network density in one network (i.e., professional or educational) increases the effect that structural holes in the other network have on the BDV's raised capital in round t.

For incremental innovation, increasing density in one network does not help increase the value of structural holes in another. Especially in the context of Big Data, where the speed of generating incremental innovations by rival is high (Dhar 2013), high network density and its associated redundancy do not help a timely response to market. Incremental innovations require quick moves to the market (Tushman and Nadler 1986), and high network density is not characterized with fast mobilization of ideas (Obstfeld 2005). Therefore, we expect:

H3: For incremental innovations, network density in one network (i.e., professional or educational) does not change the effect that structural holes in the other network have on the BDV's raised capital in round t.

High network density in both educational and professional networks can be detrimental for both radical and incremental innovations. As the network density increases in one network, it erodes value from the high density in the other. This happens because increasing network density in the second network happens at the expense of reduced structural holes; therefore, the BDV becomes deprived of information diversity needed for quality innovations. Structural holes and access to diverse knowledge are key to the development of innovation. Specifically, in the case of Big Data innovations, with their dispersed nature of knowledge (e.g., Dhar 2013), lack of structural holes reduces the quality of innovation, making them less attractive for investors. Hence, we suggest that:

H4: For both radical and incremental innovations, network density in one network (i.e., professional or educational) reduces the effect that network density in the other network has on the BDV's raised capital in round t.

High structural holes in both educational and professional networks can be detrimental for radical innovations, but not for incremental innovations. For radical innovations, as the structural holes in one network increase, the value of the other network's structural holes decreases. This happens because the structural holes in the second network emerge at the expense of reducing network cohesion. In such cases, although the BDV has access to a wide set of ideas and knowledge, it lacks the knowledge depth to come up with breakthrough ideas. Hence, we suggest:

H5: For radical innovations, structural holes in one network (i.e., professional or educational) reduces the effect that structural holes in the other network have on the BDV's raised capital in round t.

Unlike the case of radical innovations, for BDVs pursuing incremental innovations, diverse knowledge in both educational and professional networks is complementary. The quality of combinative innovation increases as a wider set of ideas (Obstfeld 2005) and innovations are inputs to the BDV's idea generation room. The content of professional knowledge about IT innovations can be different from the knowledge obtained from formal education. Thereby, BDVs with access to a broad knowledge in both educational and professional networks perform better compared to those with access in only one. Moreover, the diverse ideas obtained from one network can have higher value when combined with distinct ideas of another network. This increases the quality of idea combination, as the components of the idea combination are likely to be diverse, resulting in combinative innovations that are distinguished from those developed by rivals. Hence, we suggest that:

H6: For incremental innovations, structural holes in one network increase the effect that structural holes in the other network have on the BDV's raised capital in round t.

Figure 2 presents an overview of our research model:

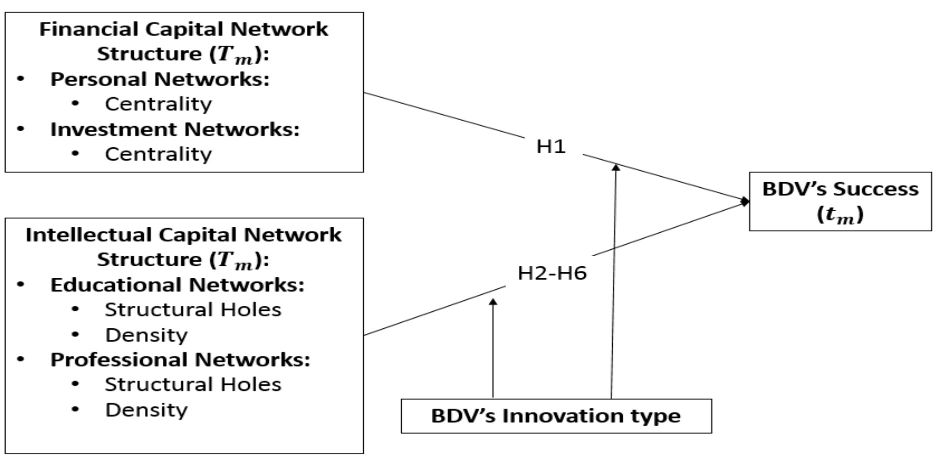


Figure 2. Research Model Overview

Methods

This research focuses on BDVs active on AngelList.com, a venture-funding website that offers a platform to new ventures so they can connect to other ventures and gain access to a pool of potential investors. A total of 2,009 BDVs were followed from January 1st, 2011 until December 29th, 2014. These ventures are self-identified as active in the Big Data context. An average BDV in our sample has raised $4.73 million, has 3.56 co-founders, and has 12.84 employees. The website assigns a profile page to each BDV where information such as names and links to personal pages of founders, employees, investors, and followers of the BDV are identified. Additionally, information regarding different rounds of capital-raising, amount of the capital raised, and contributing investors in each round is provided. Finally, the profile page includes a section where the BDV's innovation is described and introduced. Using a Python-based web-crawler, the mentioned information about each BDV is crawled and used as the main source of information. This information is then supplied by accessing the LinkedIn profile of founders, employees, and co-founders, where information about the professional and academic background, as well as the friend list of each individual, is obtained.

Obtaining Network Information

In order to define the network of ventures in our study, four different types of ties where identified to be examined. The nodes in the mapped networks are the BDVs, angels, and venture capitalists. The ego networks of each BDV consisted of ties with other BDVs, angels, and venture capitalists are analyzed to extract structural features mentioned in the hypothesis development section.

Financial Capital Network

Networks Based on Personal Ties

A tie exists between a BDV and another BDV, angel, or venture capitalist if in the periods leading to the current round of fundraising, a non-financial social transaction (e.g., friendship, followership) has happened between the two actors. The strength of ties is defined by summing the number of social interactions between each of two nodes. Specifically, following a BDV on AngelList.com by a founder or employee of another BDV, an employee of a venture capital company, or an angel is treated as a social interaction between the BDV and the other BDV, venture capitalist, or angel. Similarly, appearing in the friend list of a BDV's founder or employee by a founder or employee of another BDV, an employee of a venture capital company, or an angel is treated as another type of a social interaction between the BDV and the other BDV, the venture capitalist, or the angel. Then, the raw values of tie strength in the network are range-standardized to vary between 0 and 1.

Networks Based on Investment

A tie exists between a BDV and an angel or venture capitalist if in the periods leading to the current round of fundraising an investment, transaction has happened between the two actors. The strength of tie is the cumulated value of transactions between the two parties. Then, the raw values of tie strength in the network are range-standardized to vary between 0 and 1.

Intellectual Capital Network

Educational Network

To establish an educational tie between two BDVs, first, educational ties between all founders and employees of the sample's BDVs are determined. An educational tie between two individuals exists if they have graduated in the same major. The strength of the tie increases by one for sharing alma mater, as well as having overlap in the educational period. The strength of ties between two BDVs is determined by summing the weight of ties that exist between individuals at the two ventures. Then, the raw values of tie strength in the network are range-standardized to vary between 0 and 1.

Professional Network

To establish professional ties between two BDVs, first, professional ties between all founders and employees of the sample's BDVs are determined. A professional tie between two individuals exists if they have previously worked in the same place. The strength of the tie increases by one if the two individuals have overlapping tenures. The strength of ties between two BDVs is determined by summing the weight of ties that exist between individuals at the two ventures. Then, the raw values of tie strength in the network are range-standardized to vary between 0 and 1.

Measures

For the four networks mentioned above, structural characteristics were measured as follows. **Eigenvector centrality** is measured utilizing Bonacich's measure[16] (1972). We multiply the value of eigenvector centrality by 100 for better interpretation. On average, personal networks show an eigenvector centrality of 9.63, whereas the average eigenvector centrality in investment networks is 13.28[17]. For measuring **structural holes** and **density** measures, 1-step neighborhood ego networks of each BDV are considered. The weighted-network measures of network density and constraint suggested by Burt (2008) are utilized as measures of network density and structural holes, respectively. For measuring structural holes, we use an inverse measure of constraint. The constraint measure is calculated as follows:

$C_i = \sum_j C_{ij}$, $i \neq j$

$C_{ij} = (P_{ij} + \sum_q P_{iq} \; P_{qj})^2$, $i \neq q \neq j$

$P_{ij} = Z_{ij} / \sum_q Z_{iq}$

Where C_i is the constraint index for *i*th BDV and Z_{ij} is the weight of the tie between the *i*th and *j*th BDV. Then, P_{ij} measures the direct access to the *j*th BDV by the *i*th one. We follow

[16]The elements of the adjacency matrix are the edge weights in the whole network.

[17]We ran our models with simple degree centrality measures, instead of the eigenvector centrality measure. Although the same trends are observable with those alternative measures, Wald's chi squared of those estimations are persistently lower than the ones estimated with the eigenvector centrality measures. Therefore, we keep eigenvector centrality as the measure of financial embeddedness.

Burt's suggestion for multiplying the index by 100 for better interpretation. Also, ego network density is calculated by: Z_{ij} / N(N-1), where N is the size of the ego network. We also multiply the density ratio by 100. On average, ego networks of education in our sample show a constraint level of 27.83 and a density of 35.61. Ego networks of professional experience in our sample show a constraint level of 19.22 and a density of 24.43.

In order to determine the **innovation type** (**radical** vs. **incremental**), we conducted a text analysis of the product description section of the BDV's profile in the AngelList website, supplemented with blog and news reports about the BDV's innovation, obtained from Lexis-Nexis. We believe a BDV's innovation type can be unfolded in the product description section of the BDV's webpage because that section is the medium through which the product is introduced and its potential superiorities to competing products are explained. Further, news pieces and blog posts provide outsiders' view of the BDV's innovation. The text-mining module of R (tm) was used to analyze the product description section of each BDV's profile, as well as related news pieces and blog posts. In order to do so, first, a set of words associated with radical and incremental innovations was compiled using the existing literature on organizational innovations. We searched *Google Scholar* for articles that contained terms incremental innovation and radical innovation. Over 12,100 articles were identified, and the HTML versions of these articles where combined to form a corpus. This corpus was text-mined to extract sentences that did not include any of the radical innovation or incremental innovation with the exception of sentences that were adjacent to the sentences containing these words. Then, the sentences containing the mentioned terms and their adjacent sentences were analyzed to form a network of words that are closely associated with them.

For example, the words “original,” “breakthrough,” “pioneering,” and “groundbreaking” had the highest frequency of occurring when the word “radical innovation” was discussed in the corpus of articles. Also, the words “revise,” “extend,” “amend,” “combine,” “re-configure,” and “modify” were adjacent to the word “incremental innovation.” The adjacent words were then processed to eliminate the ones that are irrelevant to the concepts of incremental and radical innovations. Then, a library of refined word for each type of innovation was used to analyze the product description section of each BDV in the sample. The frequencies of words associated with radical and incremental innovations in the product description corpus of each BDV are calculated. The ratio of associated words to the total number of words in the text is calculated to measure emphasis on a radical vs incremental approach. The two ratios are then compared with a z-test to determine the category of innovation; the significantly larger ratio determines the category of radical or incremental innovation. Observations with insignificant z-test are dropped from further analysis. The following is a piece of a news coverage of Levyx, a Big Data startup that was evaluated as radical in our sample:

“Start up Levyx believes that its Helium and LevyxSpark platform, which is integrated into Apache Spark open source computing framework, is a groundbreaking change in big data computing. Levyx CEO Reza Sadri told Legaltech News that company’s proprietary technology can process tens of millions of queries per second on a single computing node and with latency in microseconds…
… Levyx differs from other big data processors in the market in its utilizations of solid state drives (SSD) and flash memory, which stores and erases data through electrical circuits as opposed to through mechanical parts like disk read-and-write heads in traditional hard drives, and is therefore able to process data much quicker. The use of this technology, as well running it on commodity servers, Sadri said, allows Levyx to achieve in-memory computing performance at a fraction of the cost.”

Alternatively, the following is a piece of news coverage of BloomReach which is evaluated as a BDV that pursues development of an incremental innovation:

“Big data is hot, but infrastructure-level platforms such as Hadoop, which focus on storage and processing, still need help to take them into the mainstream. They need an app or two that extend Hadoop and will let companies analyze, visualize and act on all that data without hiring a team of Stanford Ph.Ds, or that will let developers write big-data apps without having to reinvent the wheel.; BloomReach is one of those applications.

BloomReach is taking a very targeted, very hands-free approach to big data for its customers. It's offering a SaaS-based product that job listings say is for "helping leading online businesses uncover the highest quality, most relevant content sought by their consumers, when and where they want it." Founded by a team with roots at Google, Cisco, Facebook and Yahoo, among other companies, BloomReach has, according to one estimate, about 160 customers — all of them among the top 10,000 websites, and most of them in the retail space. Among its core technologies and methods are Hadoop, Lucene, Monte Carlo simulations and large-scale image processing."

The information about the **raised capital** in each round was collected from AngelList.com's profile of the BDVs. From the conception to business planning, product development, commercialization, operationalization, expansion, and eventually public offering, new ventures raise funds from different resources (e.g., Cumming 2007). 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 BDV raises external funding at multiple rounds in the same stage of development. Therefore, a new venture might have two or three rounds of seeding. In our operationalization of a fundraising period, we focus on each round of fundraising and use the raised capital in that round as the dependent variable. Then, we control for the stage at which the capital is raised.

Controls

As mentioned above, we control for the **stage of development** where the funding is raised. We do so because early and late stages of fundraising are different in terms of the funding providers,[18] as well as the amount of the capital needed.[19] To best capture the effect of the fundraising stage, for each stage of development (e.g., seeding, stage A, etc.), we specify a

[18]For example, angels contribute more in the early stages of the development, whereas venture capitalists do so in the later stages close to the initial public offering (IPO).

[19]Usually, the financial capital needed in the early stages of development are smaller than the capital needed in the later stages.

variable, the value of which indicates the number of fundraising rounds a new venture has completed in that stage, prior to the current round. Therefore, for BDVs with their first round of fundraising, the value of seeding, stage A, stage B, and stage B variables is 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.

In addition to measuring the inter-venture networks, an **intra-venture's intellectual networks** (networks among employees and founders) were also analyzed. This is because the existing research has primarily focused on intra-organizational networks as motors of innovation (e.g., Hansen 1999); therefore, we measure the network density and network constraint for all BDVs' internal networks.

Also, we control for the **number of years since a BDV has been established** because the time elapsed since establishment can have an effect on accessible financial and intellectual resources. We control for the **location dummy**, measured at the city level, whether or not the venture identifies itself as a **business-to-business (B2B)** or business-to-customer (identified by B2B tags reported in AngelList.com), and the **technological scope dummies** which represent the area of focus in the Big Data context (identified by tags reported in AngelList.com; can be analytics, security, or infrastructural). Moreover, the **number of employees**[20] (including co-founders) in the fundraising period of interest, and average of employees' (including co-founders) value of **education**[21] are controlled for.

[20] AngelList reports the date of employment and departure of employees. This data was used to calculate number of employees employed in each fundraising period.

[21] The LinkedIn account of each employee was accessed to obtain educational background of employees. The highest degree obtained by each individual was then coded (high school

Analysis

We constructed a panel where each BDV is observed in each round of fundraising (i.e., the BDVs are paneled over rounds of fundraising). This resulted in 6,810 venture-round observations.[22] We split the sample to BDVs pursuing radical and incremental innovations, and models are run within each sub-sample. For all of the models, and due to the panel structure of the data, the models are processed using a generalized least squares (GLS) estimation with panel-specific corrections for first-order auto-correlation and heteroskedasticity.

In order to test the hypothesis, we followed a step-wise approach. First, we tested the structural effects of the financial capital networks (without inclusion of the intellectual networks' variables; (1.1 and 1.2)). Next, we tested the structural effects of intellectual capital networks (without inclusion of financial capital networks' variables; (2)). Finally, we tested a full model (3) by simultaneously considering the structural variables pertaining to both financial and intellectual capital networks.

$$\begin{aligned} RaisedCapital_{it} = {} & \alpha_0 + \beta_1 * (Investment\ eigen.\ cent.)_{it} + \beta_2 * (Personal\ eigen.\ cent.)_{it} \\ & + \beta_3 * (Investment\ eigen.\ cent. * Personal\ eigen.\ cent.)_{it} + Controls + \epsilon_{it} \quad \mathbf{(1.1)} \end{aligned}$$

$$RaisedCapital_{it} = \alpha_0 + \beta_1 * (Superimposed\ eigen.\ cent.)_{it} + Controls + \epsilon_{it} \qquad \mathbf{(1.2)}$$

$$\begin{aligned} RaisedCapital\text{16F}^{23}{}_{it} = {} & \alpha_0 + \beta_1 * (SH\text{-}Edu)_{it} + \beta_2 * (D\text{-}Edu)_{it} + \beta_3 * (SH\text{-}Prof)_{it} + \beta_4 * (D\text{-}Prof)_{it} \\ & + \beta_5 * (SH\text{-}Edu * D\text{-}Prof)_{it} + \beta_6 * (D\text{-}Edu * SH\text{-}Prof)_{it} + \beta_7 * (D\text{-}Prof * D\text{-}Edu)_{it} \\ & + \beta_8 * (SH\text{-}Edu * SH\text{-}Prof)_{it} + \beta_9 * (D\text{-}Edu * SH\text{-}Edu)_{it} \\ & + \beta_{10} * (D\text{-}Prof * SH\text{-}Prof)_{it} + Controls + \epsilon_{it} \qquad \mathbf{(2)} \end{aligned}$$

---

diploma=1, associate degree= 2, undergraduate degree= 3, master's degree= 4, doctorate= 5) and averaged for each BDV.

[22] Appendix B presents the correlations among key variables.

[23] SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.

$$
\begin{aligned}
RaisedCapital_{it} = \alpha_0 &+ \beta_1 * (SH\text{-}Edu)_{it} + \beta_2 * (D\text{-}Edu)_{it} + \beta_3 * (SH\text{-}Prof)_{it} + \beta_4 * (D\text{-}Prof)_{it} \\
&+ \beta_5 * (SH\text{-}Edu * D\text{-}Prof)_{it} + \beta_6 * (D\text{-}Edu * SH\text{-}Prof)_{it} + \beta_7 * (D\text{-}Prof * D\text{-}Edu)_{it} \\
&+ \beta_8 * (SH\text{-}Edu * SH\text{-}Prof)_{it} + \beta_9 * (D\text{-}Edu * SH\text{-}Edu)_{it} \\
&+ \beta_{10} * (D\text{-}Prof * SH\text{-}Prof)_{it} + \beta_{10} * (Superimposed\ eigen.\ cent.)_{it} \\
&+ Controls + \epsilon_{it} \qquad \textbf{(3)}
\end{aligned}
$$

Table 3 represents the results of the first step, the model investigating the effect of eigenvector centrality in personal and investment networks. We start with a model that treats the two networks as structurally separate and only includes the direct effect of eigenvector centrality in each network (Model 1). Results from this model show no significant effect from either of the centrality measures in the two networks. However, when the cross-effect of eigenvector centrality in personal and investment networks is considered, a positive and significant coefficient is observed (Model 2), indicating that holding a central position among influential investors helps only when a central position in the personal networks is held. In order to examine the structural difference between the personal and investment networks, we calculate the Kendall rank correlation between eigenvector centrality in investment and personal networks (following Battiston et al. 2014). The results (Table 4) show a significantly high correlation between the two measures (0.73) indicating that the two networks are structurally convergent, thereby justifying superimposing the two networks. Hence, the two networks were superimposed, with the redundant ties between the two networks being assigned with the sum of the weights of ties in the two networks when considered separately. Also, if a tie existed in one network and not in the other, the tie was included in the superimposed network with its weight set at the original weight it had in the separated network. Then, we measured the eigenvector centrality in the newly constructed superimposed network. The results (Model 3 in Table 3) show that in BDVs pursuing both incremental and radical innovations, eigenvector centrality in the superimposed networks is positively and significantly associated with the raised capital. Taken together, the results provide support for H1.

---Insert Tables 3 and 4 here---

In the second step, we tested for the effect of structural holes and network density in both educational and professional networks. Similar to our approach investigating the financial capital networks, we started our analysis by treating the two networks structurally separate. The results of direct effect models (4 and 6 in Table 5) suggest that while the presence of structural holes in both networks positively and significantly affects the raised capital in BDVs pursing radical and incremental innovations, density does not show a significant effect in either of the networks. Also, the coefficient estimates of structural holes and density from intra-venture networks suggest a similar pattern where structural holes in both educational and professional networks show positive and significant association with the raised capital, whereas the coefficient estimate of network density in both educational and professional networks shows insignificant associations. However, our examination of the cross-effects between the networks suggests a clear trend (Models 5 and 7). For radical innovations, the interactions between educational network's density and professional network's structural holes, as well as the interaction between educational network's structural holes and professional network's density, are positive and significant, suggesting that the effect of high structural holes in one network increases with the increase in the density of the other network, supporting H2. For BDVs pursuing incremental innovations, the increase in one network's density does not increase the value of structural holes in the other (supporting H3).

Also, for BDVs in the two sub-samples, the coefficient of interaction between network density in educational and professional networks is negative and significant, indicating that network density in one network erodes value from the network density in the other, supporting H4. Moreover, for BDVs pursuing incremental innovations, the interaction of structural holes in educational and professional networks show a negative and significant association with the capital raised, indicating that increasing structural holes in one network erodes value from the structural holes present in the other, supporting H5. Finally, for BDVs pursuing incremental innovations, the coefficient of interaction between structural holes in educational and professional networks is positive and significant, indicating that structural holes in one network increase the value of structural holes in the other, supporting H6.

While we had hypothesized about the structural cross-effects of the two networks, we also control for interaction of network density and structural holes in the same network. Although the two structural measure are strongly and significantly correlated (-0.15), we controlled for these interactions to remove any effect that the co-occurrence of structural holes and network density in the same network might have. The results suggest that for incremental innovation, increasing network density in a network erodes value from the effect of its structural holes, while for radical innovation, the coefficients of interaction between density and structural holes in the same network is insignificant.

Similar to the case of financial capital networks, we compared the structural similarity of educational and professional networks. The results of the Kendall rank correlation tests (also reported in Table 3) indicate that the structural features of the two networks are diverging. The correlation between the structural holes of the two networks is 0.11 while the correlation between the densities of the two networks is 0.18. This justifies structural separation of educational and professional networks.

---Insert Table 5 here---

In the last step of our primary analysis, we include the eigenvector centrality in the superimposed financial capital network, along with the structural holes and density measures of professional and educational networks. Estimating these full models (Models 8 and 9 in Table 6) shows patterns of results that are similar to when the effects of structural positions in financial and intellectual capital networks are examined separately.

---Insert Table 6 here---

In conducting the main analysis, we established the inter-venture links by considering ties of founders as well as employees of the BDVs in the sample. However, it might be contended that founder ties are more influential in accessing both intellectual and financial capital. Founders are deemed as the main drivers of development and refinement of innovation (Amitt and Zott 2001) and also involve directly in fundraising activities (e.g., Birley 1986; Wetzel 1987; Harrison and Mason 1992; Webb et al. 2013; Thai and Turkina 2014). In order to focus on the power of founders' network, we conduct our main analysis by only considering the intellectual and financial capital networks that are defined based on founders' ties only. Models 10 and 11 in Table 7 represent these results. The findings from this table suggest that the main hypotheses hold robust when networks based on founders' ties are considered.

---Insert Table 7 here---

Sub-Sample Analysis: Technological Scope

In the context of BDVs, we define the technological scope as the main Big Data area that the BDV's product/service is focused on. Big data technologies cover diverse technological areas, most distinctively, big data security (McAfee and Brynjolfsson 2012), analytics applications (LaValle et al. 2013), and big data infrastructure (e.g., computing) (Jacobs 2009, McAfee and Brynjolfsson 2012). The review of the existing literature on Big Data suggests that Big Data technologies are also diverse in their architectural scope. While some big data technologies (e.g., cloud-based computing structures (Grossman and Siegel 2014)) are at the infrastructural level of IT architecture (see Weill and Vitale 2002 for a discussion of IT enterprise architecture) some technologies target analytics application layer (e.g., data modeling applications (Grossman and Siegel 2014)). In addition to these more pronounced technological scopes, a third scope in Big Data is concerned with the security applications that protect large operations of the Big Data innovations belonging to the two other technological scopes.

We suspect that the three scopes of BD require different levels of knowledge diversity and complexity in knowledge exchange and hence will be enabled by distinct network structures. Therefore, our general arguments regarding the mix of structural holes and network density might not be homogeneously applicable in all contexts. These scopes can be different in terms of the way the required knowledge for their development is dispersed in the network. Absent previous literature regarding these differences, we adopt an inductive approach and conduct our analyses in sub-samples corresponding to the three technological scopes. Table 8 (Models 12-17) represents the result of this sub-sample analysis.

---Insert Table 8 here---

Findings suggest that the results regarding the effect of financial capital networks' eigenvector centrality is consistent across the three scopes. However, the result shows differences when the effects of structural holes and network densities of intellectual capital networks are considered. For BDVs active in the security scope, the structure of intellectual capital network shows a pattern similar to what was observed in the full model analysis. However, while in the full sample analysis a trend was observed that structural holes in one network and network density in the other positively interact to affect raised capital for BDVs pursuing radical innovations, the subsample results show that for the BDVs in the analytics scope, only structural holes in the educational network and network density in the professional network positively and significantly interact. However, for BDVs in the infrastructural scope, only structural holes in the professional networks and network density in educational networks show the same complementary interaction. These results can be interpreted by considering that analytics innovations are built on a broader span of knowledge, from statistics to distributed computing, and thus diversity in the educational background is key to their development. In such a case, professional networks can bring the network cohesion required to transfer complex ideas needed for the development of radical innovations. On the contrary, Big Data infrastructural innovations involve a complex exchange of knowledge, mostly developed in the computer science, therefore, BDVs can benefit from high cohesion in the educational networks and obtain diverse ideas from their professional ties. Due to infrastructural innovations' dependence on the exchange of complex knowledge, increasing network density in one network does not erode value from the network density in another. Moreover, structural holes in one network do not show a significant complementarity with structural holes in another intellectual capital network.

Comparison with non-IT Context

Our hypothesizing about the effect of inter-venture networks heavily relies on the *socially-constructed* nature of IT innovations that is evidenced by the previous research. We believe the multi-disciplinary nature of IT innovations, combined with the dispersed access to the cutting-edge IT knowledge, contributes to the patterns observed in terms of the effect of intellectual capital networks. In order to further investigate this unique nature of IT innovation, we conduct our model in a different industry, i.e., Medical Device, which shows a comparable level of average valuation (i.e., $4.5 million). To allow a fair comparison between the two industries, we constructed a matched sample following suggestions of Chae et al. 2014. In doing so, for each venture-round observation in the Big Data sample, a venture-round observation in the Medical Device context was selected that was in the 0.30% range of employee size and level of employee education, and share the same year of establishment with the venture from the Big Data Sample. Due to the restrictions for building the matched sample, the sample in the Medical Devices context had fewer observations (5,182).[24]

We start our matched sample analysis by assuming that similar to the Big Data context, personal and investment networks have similar structure, whereas educational and professional networks are structurally distinct. Therefore, we replicated our full models (Models 8 and 9) for the Medical Devices sample (Models 18 and 19 in Table 9). While in both Big Data and Medical Devices sample eigenvector centrality in the financial capital market is positively and significantly associated with raised capital, the results for the effect of intellectual capital networks' structure on capital raised are not converging.

---Insert Table 9 here---

A possible explanation for such a difference between the two industries is the difference in the structural similarity of educational and professional networks. To investigate this possible explanation, we first calculate the Kandall correlation coefficient for structural features of networks in the Medical Devices industry. The results (Table 10) show that although personal and investment networks are structurally similar (similar to the Big Data context), there is also a high correlation between the structural features of educational and professional networks. Specifically, the correlation coefficient between structural holes in educational and professional networks is 0.46, and the correlation coefficient between network densities in the two networks

[24] Only observations that had a match in the Big Data sample were included.

in 0.38. This indicates that the structural separation of educational and professional networks in the Medical Devices context might be misleading. To address this issue, we superimpose the educational and professional networks in the Medical Devices context and calculate the network density, structural holes, and interaction between the two based on a single network of intellectual capital.

---Insert Table 10 here---

The results of this modified model are also presented in Table 9 (Models 20 and 21). The findings show insignificant coefficients for structural holes, density, and the interaction of the two for inter-venture networks. However, the results indicate that while intra-venture structural holes in ventures pursuing both radical and incremental innovations are positively and significantly associated with the raised capital, the intra-venture network density has a positive and significant association with the raised capital only for radical innovations. Taken together, these results indicate two distinctions between the intellectual capital networks in Big Data and Medical Devices industries. First, educational and professional networks in the Big Data industry are structurally distinct, whereas the two networks show similar characteristics in the Medical Devices context. Second, while in the Big Data context inter-venture intellectual networks contribute to the capital raised, therefore providing evidence for their socially-constructed nature, in the Medical Devices context, only intra-venture intellectual capital networks contribute to the raised capital.

Network Effects on Inception of Innovation

Thus far, we have viewed intellectual networks as mediums through which BDVs access knowledge resources required to refine and further develop their initial idea. It is also possible that educational and professional ties of entrepreneurs affect the radicalness of innovation at its inception. In order to test for such an effect, we investigate the effect of intellectual networks' structure on whether a BDV pursues a radical or incremental innovation. Specifically, we consider the educational and professional ties of the founders of a BDV one year before establishment. Since we need access to data about existing BDVs one year prior to establishment of a focal one, this analysis is done on BDVs established after January 1st 2012. Table 11 presents two models (Models 22 and 23) with direct and interaction effects of inter-venture educational and professional networks' structure.

---Insert Table 11 here---

The results suggest that network density or structural holes alone do not affect the type of innovation a BDV pursues. However, the coefficients of the interaction between network density in one network and structural holes in other are positive and significant. Therefore, as the network density in one intellectual capital network increases, it increases the positive effect that structural holes have on a BDV's pursuit of radical innovations. Moreover, the results show as the structural holes in one network increase, it increases the likelihood that structural holes in another leads to a BDV's pursuit of incremental innovations. Figure 3 presents the emerging model from our study.

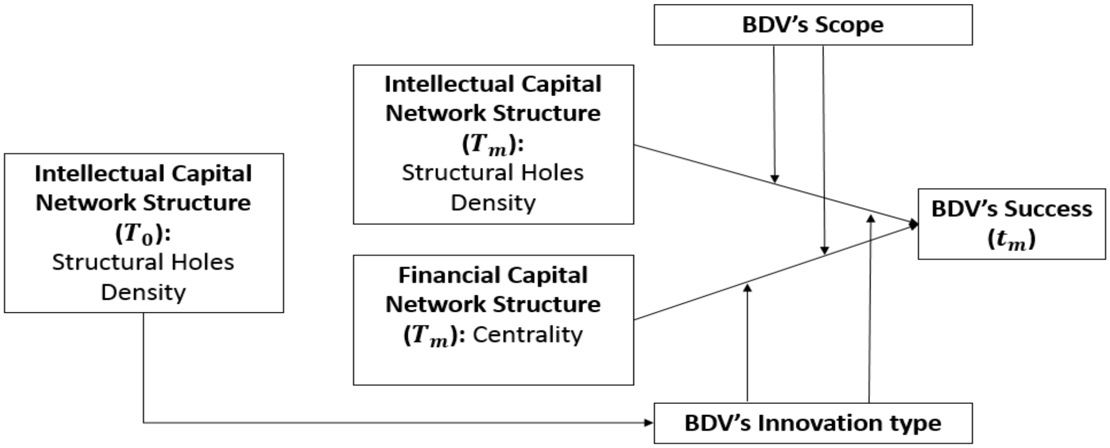


Figure 3. Emerging Research Model

Discussion

Focusing on BDVs, this study investigates the effect that intellectual and financial capital networks have on a new venture's success, in terms of the raised capital in a fundraising period. Specifically, educational and professional networks are identified as structurally distinct networks that facilitate the flow of knowledge resources to BDVs for improvement and development of their innovation. The results suggest that for radical innovations, one of the educational or professional networks can supply the BDV with structural holes, enabling access to *diverse ideas*, and the other can provide the network density needed to exchange complex knowledge required for development of *novel ideas*. Moreover, our findings suggest that for incremental innovations, diverse ideas obtained from educational networks can complement those obtained from professional ties. Specifically, these effects are persistent for ties made by founders only, or when extended ties among venture employees are also considered. Moreover, the results suggest that intellectual networks of founders can affect the type of innovation, radical or incremental, at the inception stage. Also, we found that depending on the technological scope, the structural features of intellectual networks required for success change.

In addition to the effects of intellectual capital networks, our results suggest that personal ties with other BDVs' founders and employees, personal ties made with angels and capitalists, and ties based on previous investments are pertinent for raising capital. Specifically, we found that eigenvector centrality in the financial capital network positively, significantly, and consistently predicts the BDV's success.

Finally, our findings provide evidence that unlike the case of the Big Data context, inter-venture intellectual networks do not contribute to fundraising success in a comparable non-IT context, i.e., Medical Devices. The results suggest that while innovations are socially constructed in the context of IT generally, and Big Data specifically, this is not always the case, as evidence by lack of support for effects of inter-venture intellectual capital networks in the context of Medical Devices. Further, the results indicate that unlike the case in the IT context, educational and professional networks are not structurally distinct in a non-IT context such as Medical Devices.

Contributions

Primarily, this study contributes to the literature on IT innovations (e.g., Nambisan et al. 1999; Fichman 2001, Han et al. 2012) which has mostly examined them in the context of established firms (Han et al. 2012). However, with innovations generated by new ventures becoming increasingly important in the IT field, this study extends the literature by focusing on innovations generated in new ventures and providing a network framework that explains the success of the innovation. Specifically, this study shows that IT innovations are socially-constructed through intellectual networks of association that exist among venture in an industry.

Moreover, this study documents that such social embeddedness of innovation is not prevalent in other non-IT contexts.

Second, while the general literature on new ventures' success has mainly focused on the networks that help obtaining financial and reputational resources, this study extends this network view by empirically providing evidence that external *intellectual ties* with other new ventures also contribute to the success of a focal new venture, especially for those ventures that are still at the early stages of development. Specifically, in the IT context, our results provide evidence for how innovations can be socially developed and refined through intellectual ties among new ventures in the same industry. Also, the study suggests that while intellectual networks operate as a *driving* factor for pursuit of certain types innovations in the conception stages, they operate as a factor that *interacts* with that type of innovation (radical or incremental) to predict financial success.

Third, this study extends the network research in new ventures that has mainly focused on aggregated networks (Lechner et al. 2006), by introducing separate networks and distinguishing the structural interplay between them. More importantly, we show an empirical approach that depends on the structural similarities to aggregate or disaggregate distinct network ties. An implication of disaggregating inter-venture networks is resolving the equivocal suggestions made by previous research. For example, while anecdotal evidence (e.g., Elfring and Hulsink 2003) suggest that a mix of structural holes and network cohesion is required for success of radical innovations, co-presence of the two structural features in a singular network is unlikely to happen. However, considering ties with different contents as distinct, we showed that a new venture can access structural holes in one network and simultaneously access cohesion in another.

Practical Implications

From a practical perspective, this study has a number of implications. First, the results of the study inform entrepreneurs and incubator managers about networking strategies contingent with the type of innovation a new venture pursues. Specifically, our findings suggest that intellectual ties should be appropriated by considering the radicalness of the innovation a new venture pursues. Figures 4a and 4b present a blue print for networking structures appropriate for each type of innovation. Another implication of this study is for incubator firms. Incubator firms mainly focus on providing new ventures with networking opportunities that connect entrepreneurs with angels and venture capitalists. However, findings of our study suggest that personal ties with employees that founders of other BDVs can also contribute to fundraising success.

Also, our findings suggest that networking efforts for obtaining financial and reputational resources can be extended by developing proper intellectual links, by considering the educational and professional background of new recruitments. Specifically, our findings suggest that ventures pursuing incremental innovations need to diversify both of their educational and professional backgrounds. Moreover, ventures pursuing radical innovations should consider building a dense network of one type, e.g., educational, and supplement this dense network with a diverse network of another type, e.g., professional. These findings also provide investors with additional information to evaluate success of new ventures. Since access to financial capital is key to new ventures' success, and since intellectual capital networks play a key role in a new venture at development stages, investors can evaluate the promise of the venture by considering its embeddedness in intellectual networks, while taking into account the radicalness of innovation pursued by the venture.

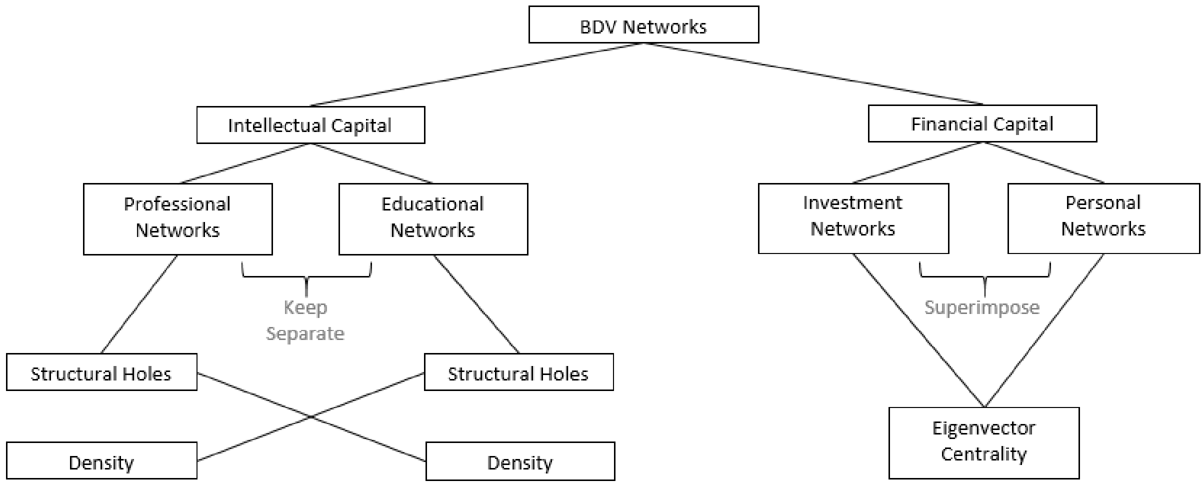


Figure 4a. Networking Structure Appropriate for BDVs Pursuing Radical Innovations

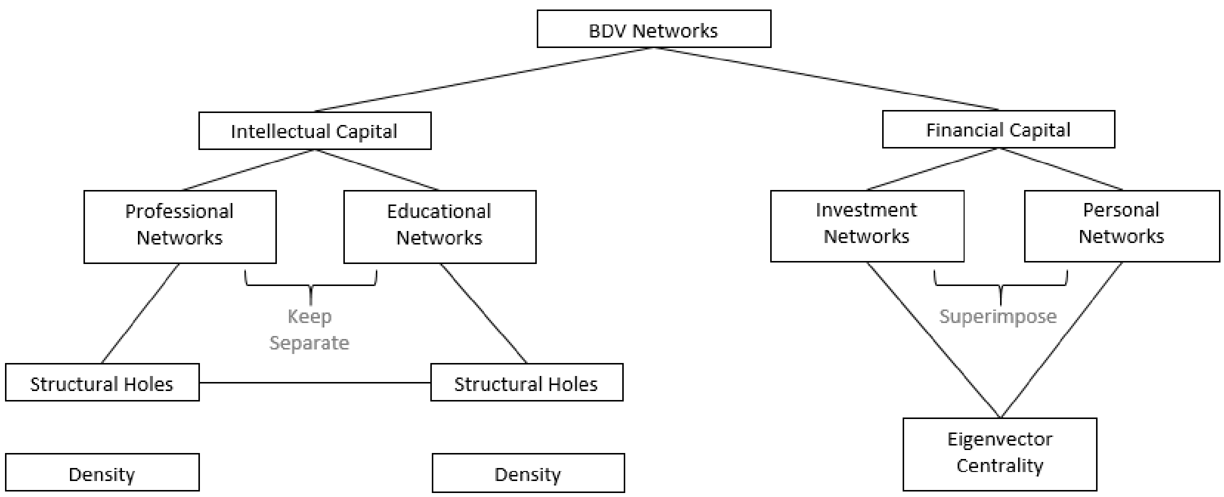


Figure 4b. Networking Structure Appropriate for BDVs Pursuing Incremental Innovations

Limitations

In spite of its contributions, the findings of the study should be interpreted considering its limitations. First, we use the BDVs listed on AngelList.com and ties evidenced in the website and LinkedIn to construct financial capital and intellectual capital networks. While it is possible that some ties are omitted due to the incomplete information in the website or due to lack of access to BDVs that are not present in the AngelList.com, threat of tie or node omission is a well-known limitation of network studies. However, we are encouraged by the number of BDVs studied that is considerably higher than the sample size in similar studies. Also, in studying intellectual capital networks, we focused on educational and professional networks of association. We were limited in our access to other types of intellectual associations such as journal memberships or attendance to field-related conferences. We suggest that future research investigates other types of intellectual association and evaluate the role they have in raising financial resources. Moreover, in identifying the radicalness of innovations, we rely on a venture's description of a product as well as news report and blog posts about it. Self-descriptions and news coverage might be biased towards claiming a product/service radical. However, we strongly believe that our approach might contain less bias compared to the alternative approaches used, such as self-reported measures. Moreover, while the interaction between different network structures provides evidence of symmetrical complementarity between structural holes and network density for BDVs pursuing radical innovations, the theoretical arguments point to the possibility of a sequential complementarity. While studying this sequential complementarity is out of this study' scope, we encourage future studies to further investigate it.

Finally, in our matched sample comparison with non-IT contexts, we had only investigated one other context, i.e., Medical Devices, mainly due to the limitations in accessing another industry present in AngelList.com with similar valuation range and enough observations to make meaningful comparisons. We believe that further research is required to further examine the uniqueness of the effect of inter-venture intellectual networks to the IT context.

References

Amit, R., and C. Zott. 2001, "Value Creation in e-business," *Strategic Management Journal* (22:6-7), pp. 493-520.

Battiston, F., V. Nicosia, and V. Latora. 2014, "Structural Measures for Multiplex Networks," *Physical Review E* (89:3), pp. 032804.

Baum, J. A., T. Calabrese, and B. S. Silverman. 2000, "Don't Go it Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology," *Strategic Management Journal* (21:3), pp. 267-294.

Bhide, A., and H. Stevenson. 1992, "Trust, Uncertainty, and Profit," *The Journal of Socio-Economics* (21:3), pp. 191-208.

Birley, S. 1986, "The Role of Networks in the Entrepreneurial Process," *Journal of Business Venturing* (1:1), pp. 107-117.

Bloodgood, J. M., H. J. Sapienza, and A. L. Carsrud. 1995, "The Dynamics of New Business Start-Ups: Person, Context, and Process," *Advances in Entrepreneurship, Firm Emergence and Growth* (2), pp. 123-144.

Bonacich, P. 1972, "Factoring and Weighting Approaches to Status Scores and Clique Identification," *Journal of Mathematical Sociology* (2:1), pp. 113-120.

Brajkovich, L. F. 1994, "Sources of Social Structure in a Start-Up Organization: Work Networks, Work Activities, and Job Status," *Social Networks* (16:3), pp. 191-212.

Brüderl, J., and P. Preisendörfer. 1998, "Network Support and the Success of Newly Founded Business," *Small Business Economics* (10:3), pp. 213-225.

Burt, R. 2008, "Measuring Access to Structural Holes," *University of Chicago Graduate School of Business, Chicago*.

Burt, R. S. 2004, "Structural Holes and Good ideas1," *American Journal of Sociology* (110:2), pp. 349-399.

———. 2009. *Structural Holes: The Social Structure of Competition*, Harvard university press.

Casper, S. 2007, "How do Technology Clusters Emerge and Become Sustainable?: Social Network Formation and Inter-Firm Mobility within the San Diego Biotechnology Cluster," *Research Policy* (36:4), pp. 438-455.

Chae, H., C. E. Koh, and V. R. Prybutok. 2014, "Information Technology Capability and Firm Performance: Contradictory Findings and their Possible Causes." *MIS Quarterly* (38:1), .

Chen, H., R. H. Chiang, and V. C. Storey. 2012, "Business Intelligence and Analytics: From Big Data to Big Impact." *MIS Quarterly* (36:4), pp. 1165-1188.

Chen, X., X. Yao, and S. Kotha. 2009, "Entrepreneur Passion and Preparedness in Business Plan Presentations: A Persuasion Analysis of Venture Capitalists' Funding Decisions," *Academy of Management Journal* (52:1), pp. 199-214.

Clarysse, B., M. Knockaert, and A. Lockett. 2007, "Outside Board Members in High Tech Start-Ups," *Small Business Economics* (29:3), pp. 243-259.

Couger, J. D. 1973, "Curriculum Recommendations for Undergraduate Programs in Information Systems," *Communications of the ACM* (16:12), pp. 727-749.

Cumming, D. 2007, "Government Policy Towards Entrepreneurial Finance: Innovation Investment Funds," *Journal of Business Venturing* (22:2), pp. 193-235.

Dhar, V. 2013, "Data Science and Prediction," *Communications of the ACM* (56:12), pp. 64-73.

Elfring, T., and W. Hulsink. 2003, "Networks in Entrepreneurship: The Case of High-Technology Firms," *Small Business Economics* (21:4), pp. 409-422.

Ettlie, J. E., W. P. Bridges, and R. D. O'keefe. 1984, "Organization Strategy and Structural Differences for Radical Versus Incremental Innovation," *Management Science* (30:6), pp. 682-695.

Ferrary, M. 2003, "The Gift Exchange in the Social Networks of Silicon Valley," *California Management Review* (45:4), pp. 120-138.

Fichman, R. G. 2001, "The Role of Aggregation in the Measurement of IT-Related Organizational Innovation," *MIS Quarterly*pp. 427-455.

Florin, J., M. Lubatkin, and W. Schulze. 2003, "A Social Capital Model of High-Growth Ventures," *Academy of Management Journal* (46:3), pp. 374-384.

Gilbert, B. A., P. P. McDougall, and D. B. Audretsch. 2008, "Clusters, Knowledge Spillovers and New Venture Performance: An Empirical Examination," *Journal of Business Venturing* (23:4), pp. 405-422.

Glückler, J., and T. Armbrüster. 2003, "Bridging Uncertainty in Management Consulting: The Mechanisms of Trust and Networked Reputation," *Organization Studies* (24:2), pp. 269-297.

Goes, P. B. 2014, "Editor's Comments: Big Data and IS Research," *Mis Quarterly* (38:3), pp. iii-viii.

Gargiulo, M., and M. Benassi. 1999. *"The Dark Side of Social Capital," Corporate Social Capital and Liability,* Anonymous Springer, pp. 298-322.

Granovetter, M. 1973, "The Strength of Weak Ties," *American Journal of Sociology* (78:6), pp. l.

Grossman, R. L., and K. P. Siegel. 2014, "Organizational Models for Big Data and Analytics," *Journal of Organization Design* (3:1), pp. 20-25.

Hallen, B. L., and K. M. Eisenhardt. 2012, "Catalyzing Strategies and Efficient Tie Formation: How Entrepreneurial Firms Obtain Investment Ties," *Academy of Management Journal* (55:1), pp. 35-70.

Han, K., W. Oh, K. S. Im, R. M. Chang, H. Oh, and A. Pinsonneault. 2012, "Value Cocreation and Wealth Spillover in Open Innovation Alliances," *MIS Quarterly* (36:1), pp. 291-325.

Hanneman, R. A., and M. Riddle. 2005, *Introduction to Social Network Methods*.

Hansen, E. L. 1995, "Entrepreneurial Networks and New Organization Growth," *Entrepreneurship: Theory and Practice* (19:4), pp. 7-20.

Hansen, M. T. 1999, "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits," *Administrative Science Quarterly* (44:1), pp. 82-111.

Harrison, R. T., and C. M. Mason. 1992, "International Perspectives on the Supply of Informal Venture Capital," *Journal of Business Venturing* (7:6), pp. 459-475.

Hite, J. M., and W. S. Hesterly. 2001, "The Evolution of Firm Networks: From Emergence to Early Growth of the Firm," Strategic Management Journal (22:3), pp. 275-286.

Hoang, H., and B. Antoncic. 2003, "Network-Based Research in Entrepreneurship: A Critical Review," *Journal of Business Venturing* (18:2), pp. 165-187.

Hsu, D. H. 2004, "What do Entrepreneurs Pay for Venture Capital Affiliation?" *The Journal of Finance* (59:4), pp. 1805-1844.

Inge Jenssen, J., and A. Greve. 2002, "Does the Degree of Redundancy in Social Networks Influence the Success of Business Start-Ups?" *International Journal of Entrepreneurial Behavior & Research* (8:5), pp. 254-267.

Jacobs, A. 2009, "The Pathologies of Big Data," *Communications of the ACM* (52:8), pp. 36-44.

Jenssen, J. I., and H. F. Koenig. 2002, "The Effect of Social Networks on Resource Access and Business Start-Ups," *European Planning Studies* (10:8), pp. 1039-1046.

Johannisson, B., 2000, ‘Networking and Entrepreneurial Growth’, in D. L. Sexton and H. Landström (eds.), The Blackwell Handbook of Entrepreneurship, Oxford: Blackwell.

Johannisson, B., O. Alexanderson, K. Nowicki, and K. Senneseth. 1994, "Beyond Anarchy and Organization: Entrepreneurs in Contextual Networks," *Entrepreneurship & Regional Development* (6:4), pp. 329-356.

Kautz, K., S. Madsen, and J. Nørbjerg. 2007, "Persistent Problems and Practices in Information Systems Development," *Information Systems Journal* (17:3), pp. 217-239.

Knill, A. 2009, "Should Venture Capitalists Put all their Eggs in One Basket? Diversification Versus Pure-Play Strategies in Venture Capital," *Financial Management* (38:3), pp. 441-486.

Kollmann, T., and A. Kuckertz. 2010, "Evaluation Uncertainty of Venture Capitalists' Investment Criteria," *Journal of Business Research* (63:7), pp. 741-747.

Krackhardt, D., 1992, “The Strength of Strong Ties: The Importance of Philos in Organizations,” in N. Nohria and R. G. Eccles (eds.), *Networks and Organizations:Structure, Form and Action*, Cambridge, MA: HBS Press, pp. 216–239.

Kuemmerle, W. 2002, "Home Base and Knowledge Management in International Ventures," *Journal of Business Venturing* (17:2), pp. 99-122.

LaValle, S., E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz. 2013, "Big Data, Analytics and the Path from Insights to Value," *MIT Sloan Management Review* (21:.

Lechner, C., M. Dowling, and I. Welpe. 2006, "Firm Networks and Firm Development: The Role of the Relational Mix," *Journal of Business Venturing* (21:4), pp. 514-540.

MacMillan, I. C., R. Siegel, and P. S. Narasimha. 1986, "Criteria used by Venture Capitalists to Evaluate New Venture Proposals," *Journal of Business Venturing* (1:1), pp. 119-128.

Maurer, I., and M. Ebers. 2006, "Dynamics of Social Capital and their Performance Implications: Lessons from Biotechnology Start-Ups," *Administrative Science Quarterly* (51:2), pp. 262-292.

McAfee, A., and E. Brynjolfsson. 2012, "Big Data: The Management Revolution," *Harvard Business Review* (90:10), Oct, pp. 60-6, 68, 128.

McPherson, M., L. Smith-Lovin, and J. M. Cook. 2001, "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology*pp. 415-444.

Mehra, A., A. L. Dixon, D. J. Brass, and B. Robertson. 2006, "The Social Network Ties of Group Leaders: Implications for Group Performance and Leader Reputation," *Organization Science* (17:1), pp. 64-79.

Nambisan, S., R. Agarwal, and M. Tanniru. 1999, "Organizational Mechanisms for Enhancing User Innovation in Information Technology," *MIS Quarterly*pp. 365-395.

Obstfeld, D. 2005, "Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation," *Administrative Science Quarterly* (50:1), pp. 100-130.

Ostgaard, T. A., and S. Birley. 1996, "New Venture Growth and Personal Networks," *Journal of Business Research* (36:1), pp. 37-50.

Pirolo, L., and M. Presutti. 2010, "The Impact of Social Capital on the Start-ups' Performance Growth," *Journal of Small Business Management* (48:2), pp. 197-227.

Powell, W. W., K. W. Koput, and L. Smith-Doerr. 1996, "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology," *Administrative Science Quarterly*pp. 116-145.

Preston, D. S., and E. Karahanna. 2009, "Antecedents of IS Strategic Alignment: A Nomological Network," *Information Systems Research* (20:2), pp. 159-179.

Rosenbusch, N., J. Brinckmann, and A. Bausch. 2011, "Is Innovation always Beneficial? A Meta-Analysis of the Relationship between Innovation and Performance in SMEs," *Journal of Business Venturing* (26:4), pp. 441-457.

Rowley, T., D. Behrens, and D. Krackhardt. 2000, "Redundant Governance Structures: An Analysis of Structural and Relational Embeddedness in the Steel and Semiconductor Industries," *Strategic Management Journal* (21:3), pp. 369-386.

Saxenian, A. 1990, "Regional Networks and the Resurgence of Silicon Valley," *California Management Review* (33:1), pp. 89-112.

Smith, K. G., C. J. Collins, and K. D. Clark. 2005, "Existing Knowledge, Knowledge Creation Capability, and the Rate of New Product Introduction in High-Technology Firms," *Academy of Management Journal* (48:2), pp. 346-357.

Sørensen, M. 2007, "How Smart is Smart Money? A two-sided Matching Model of Venture Capital," *The Journal of Finance* (62:6), pp. 2725-2762.

Starr, J. A., and I. C. MacMillan. 1990, "Resource Cooptation via Social Contracting: Resource Acquisition Strategies for New Ventures," *Strategic Management Journal* (11:4), pp. 79-92.

Steier, L., and R. Greenwood. 2000, "Entrepreneurship and the Evolution of Angel Financial Networks," *Organization Studies* (21:1), pp. 163-192.

Thai, M. T. T., and E. Turkina. 2014, "Macro-Level Determinants of Formal Entrepreneurship Versus Informal Entrepreneurship," *Journal of Business Venturing* (29:4), pp. 490-510.

Timmons, J. A., and W. D. Bygrave. 1986, "Venture Capital's Role in Financing Innovation for Economic Growth," *Journal of Business Venturing* (1:2), pp. 161-176.

Tushman, M., and D. Nadler. 1986, "Organizing for Innovation," *California Management Review* (28:3), pp. 74-92.

Uzzi, B. 1999, "Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing," *American Sociological Review*pp. 481-505.

———. 1997, "Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness," *Administrative Science Quarterly*pp. 35-67.

Van Praag, M., A. Van Witteloostuijn, and J. Van der Sluis. 2013, "The Higher Returns to Formal Education for Entrepreneurs Versus Employees," *Small Business Economics* (40:2), pp. 375-396.

Wang, P., and N. C. Ramiller. 2009, "Community Learning in Information Technology Innovation," *Mis Quarterly* (33:4), pp. 709-734.

Webb, J. W., G. D. Bruton, L. Tihanyi, and R. D. Ireland. 2013, "Research on Entrepreneurship in the Informal Economy: Framing a Research Agenda," *Journal of Business Venturing* (28:5), pp. 598-614.

Weill, P., and M. Vitale. 2002, "What IT Infrastructure Capabilities are Needed to Implement e-Business Models?" *Mis Quarterly* (1:1), pp. 17.

Wetzel, W. E. 1987, "The Informal Venture Capital Market: Aspects of Scale and Market Efficiency," *Journal of Business Venturing* (2:4), pp. 299-313.

Witt, P. 2004, "Entrepreneurs' Networks and the Success of Start-Ups," *Entrepreneurship & Regional Development* (16:5), pp. 391-412.

Zott, C., and R. Amit. 2007, "Business Model Design and the Performance of Entrepreneurial Firms," *Organization Science* (18:2), pp. 181-199.

Tables of Chapter 3

Table 1- Summary of the potentials of networks structures with high levels of structural holes and network cohesion.

	Potential for reach to diverse knowledge	Potential for enabling exchange of complex knowledge
Structural holes	H	L
Network cohesion	L	H

Table 2- Type of innovation and the fostering network structure

	Incremental innovations	Radical innovations
Structural holes	H	H
Network cohesion	L	H

Table 3- The Effect of Financial Capital Networks

	Networks treated separately				**Superimposed networks**	
	Incremental		**Radical**		**Incremental**	**Radical**
DV =Raised Capital	**Model 1**		**Model 2**		**Model 3**	
Investment eigen. cent.	0.012	0.009	0.004	0.003		
Personal eigen. cent.	0.022	0.018	0.019	0.018		
Investment eigen. cent.* Personal eigen. cent.		0.083*		0.072*		
Superimposed eigen. cent.					0.182***	0.178***
Wald's Chi	*1073.86*	*1112.52*	*1008.92*	*1161.14*	*2252.22*	*2371.34*
N	*2712*	*2712*	*4098*	*4098*	*2712*	*4098*

Coefficients of variables number of employees, education of employees, number of years the BDV is established, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 4- Kendall Correlation of Different Networks' Structural Features

	Correlation	
SH-Edu - SH-Prof	0.11[#]	Justifies separation
D-Edu - D-Edu	0.18*	Justifies separation
SH-Edu - SH-Prof (IVN)	0.21*	Justifies separation
D-Edu - D-Edu (IVN)	0.14	Justifies separation
Investment eigen. cent. - Personal eigen. cent.	0.73**	Justifies superimposing

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
*#p < 0.10, * p < 0.05, ** p < 0.01;*

Table 5- The Effect of Intellectual Capital Networks

	Incremental		Radical	
DV= capital raised	**Model 4**	**Model 5**	**Model 6**	**Model 7**
SH-Edu	0.114***	0.082**	0.0131***	0.182***
D-Edu	-0.021	0.005	0.012	0.019
SH-Prof	0.153***	0.093**	0.096**	0.149***
D-Prof	-0.019	0.008	0.009	0.012
SH-Edu * D-Prof		0.011		0.173***
D-Prof * D-Edu		-0.076**		-0.082**
SH-Edu * SH-Prof		0.132***		-0.078*
D-Edu * SH-Prof		0.016		0.125***
D-Edu * SH-Edu		-0.038*		0.014
D-Prof * SH-Prof		-0.026#		0.008
IVN D- Prof	0.008	0.005	0.022*	0.052*
IVN D- Edu	0.014	0.017	0.031*	0.063*
IVN SH- Prof	0.098**	0.073*	0.097*	0.096**
IVN SH- Edu	0.086*	0.082*	0.110**	0.084*
Wald's Chi	*3026.34*	*5783.67*	*3244.38*	*6111.32*
N	*2712*	*2712*	*4098*	*4098*

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.

Coefficients of variables number of employees, education of employees, number of years the BDV is established, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;

*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*

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

Table 6- The Effect of Both Financial Capital and Intellectual Capital Networks

	Incremental	Radical
DV= capital raised	**Model 8**	**Model 9**
SH-Edu	0.098**	0.080*
D-Edu	0.008	0.015
SH-Prof	0.120***	0.089**
D-Prof	0.017	0.012
SH-Edu * D-Prof	-0.010	0.168***
D-Prof * D-Edu	-0.114**	-0.053*
SH-Edu * SH-Prof	0.129***	-0.074*
D-Edu * SH-Prof	0.012	0.059**
D-Edu * SH-Edu	-0.037**	0.008
D-Prof * SH-Prof	-0.019*	0.011
IVN D- Prof	0.008	0.033*
IVN D- Edu	0.009	0.035*
IVN SH- Prof	0.056*	0.073*
IVN SH- Edu	0.068*	0.082**
Superimposed eigen. cent.	0.201***	0.188***
Wald's Chi	*7812.39*	*8623.91*
N	*2712*	*4098*

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
Coefficients of variables number of employees, education of employees, number of years the BDV is established, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 7- Full Model When Only Founders' Ties Are Considered

	Incremental	Radical
DV= capital raised	**Model 10**	**Model 11**
SH-Edu	0.083*	0.053*
D-Edu	0.011	0.009
SH-Prof	0.117***	0.144***
D-Prof	0.020	0.018
SH-Edu * D-Prof	0.013	0.128***
D-Prof * D-Edu	-0.162***	-0.099**
SH-Edu * SH-Prof	0.133***	-0.051*
D-Edu * SH-Prof	0.008	0.071*
D-Edu * SH-Edu	-0.020#	0.008
D-Prof * SH-Prof	-0.018*	0.003
IVN D- Prof	0.010	-0.003
IVN D- Edu	0.002	0.009
IVN SH- Prof	0.005	0.012
IVN SH- Edu	0.007	0.005
Superimposed eigen. cent.	0.202***	0.192***
Wald's Chi	*6794.31*	*7032.46*
N	*2712*	*4098*

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
Coefficients of variables number of employees, education of employees, number of years the BDV is established, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 8- Sub-sample Analysis: Technological Scope

	Analytics		Security		Infrastructure	
	Incremental	Radical	Incremental	Radical	Incremental	Radical
DV= capital raised	**Model 12**	**Model 13**	**Model 14**	**Model 15**	**Model 16**	**Model 17**
SH-Edu	0.081**	0.072*	0.082**	0.061*	0.071*	0.096**
D-Edu	0.005	0.006	0.012	0.007	0.005	0.014
SH-Prof	0.098**	0.067*	0.092**	0.042*	0.089**	0.092*
D-Prof	0.010	0.013	0.008	0.010	0.019	0.007
SH-Edu * D-Prof	-0.017	0.191***	-0.011	0.111**	-0.011	0.019
D-Prof * D-Edu	-0.211***	-0.103**	-0.080*	-0.051*	-0.017	-0.011
SH-Edu * SH-Prof	0.173***	-0.078**	0.062**	-0.074*	0.016	-0.059*
D-Edu * SH-Prof	0.005	0.017	0.003	0.063*	0.016	0.084**
D-Edu * SH-Edu	-0.021*	0.001	-0.018*	0.010	-0.021	0.001
D-Prof * SH-Prof	-0.014#	-0.002	-0.012#	0.010	-0.011	-0.012
IVN D- Prof	0.003	0.041*	0.005	0.027*	0.003	0.044**
IVN D- Edu	-0.004	0.056**	0.009	0.019#	0.009	0.022*
IVN SH- Prof	0.028*	0.081*	0.071*	0.082**	0.042*	0.108**
IVN SH- Edu	0.072**	0.090*	0.052*	0.091*	0.033**	0.094**
Superimposed eigen. cent.	0.194***	0.170***	0.173***	0.231***	0.221***	0.211***
Wald's Chi	*6232.12*	*7002.56*	*6714.81*	*6537.79*	*7444.31*	*7518.29*
N	*982*	*1349*	*699*	*1030*	*1031*	*1719*

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
Coefficients of variables number of employees, education of employees, number of years the BDV is established, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 9- Matched Sample Comparison with Medical Devices Industry

	Big Data		Medical Devices			
	Incremental	Radical	Incremental	Radical	Incremental	Radical
DV= capital raised	Model 8	Model 9	Model 18	Model 19	Model 20	Model 21
SH-Edu	0.098**	0.080*	0.012	0.010		
D-Edu	0.008	0.015	0.009	0.007		
SH-Prof	0.120***	0.089**	0.002	0.007		
D-Prof	0.017	0.012	0.005	0.014		
SH-Edu * D-Prof	-0.010	0.168***	0.011	0.016		
D-Prof * D-Edu	-0.114**	-0.053*	0.005	0.008		
SH-Edu * SH-Prof	0.129***	-0.074*	0.005	0.005		
D-Edu * SH-Prof	0.012	0.059**	0.003	0.009		
D-Edu * SH-Edu	-0.037**	0.008	-0.007	0.011		
D-Prof * SH-Prof	-0.019*	0.011	-0.004	0.010		
IVN D- Prof	0.008	0.033*	0.003	0.004		
IVN D- Edu	0.009	0.035*	0.005	0.000		
IVN SH- Prof	0.056*	0.073*	-0.006	0.003		
IVN SH- Edu	0.068*	0.082**	-0.008	0.011		
Superimposed SH					0.012	0.009
Superimposed D					0.007	-0.007
Superimposed SH * D					0.000	0.003
Superimposed IVN SH					0.086**	0.092*
Superimposed IVN D					0.019	0.039**
Superimposed eigen. cent.	0.201***	0.188***	0.294***	0.376***	0.271***	0.301***
Wald's Chi	*7812.39*	*8623.91*	*4324.81*	*4526.72*	*5679.34*	*6103.38*
N	*2712*	*4098*	*1954*	*3228*	*1954*	*3228*

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
Coefficients of variables number of employees, education of employees, number of years the BDV is established, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, funding series (i.e., no stage, seed, A, B, C), and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 10- Comparison of Kendall Rank Correlation Results

	Medical Devices	Big Data Benchmark
SH-Edu - SH-Prof	0.46***	0.11#
D-Edu - D-Edu	0.38**	0.18*
SH-Edu - SH-Prof (IVN)	0.54**	0.21*
D-Edu - D-Edu (IVN)	0.28*	0.14
Investment eigen. cent. - Personal eigen. cent.	0.75***	0.73**

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001.*

Table 11- The Network Effect at the Inception Phase

DV= Radical Innovation	Model 22	Odds Ratio	Model 23	Odds Ratio
SH-Edu	0.016	1.016	0.018	1.018
D-Edu	0.008	1.008	0.010	1.010
SH-Prof	0.015	1.015	0.007	1.007
D-Prof	0.004	1.004	0.007	1.007
SH-Edu * D-Prof			0.139***	1.149
D-Prof * D-Edu			0.002	1.002
SH-Edu * SH-Prof			-0.120***	0.887
D-Edu * SH-Prof			0.151***	1.163
D-Edu * SH-Edu			0.013	1.013
D-Prof * SH-Prof			0.015	1.015
IVN D- Prof	0.028*	1.028	0.034*	1.035
IVN D- Edu	0.021*	1.021	0.029**	1.029
IVN SH- Prof	0.008	0.005	0.011	0.010
IVN SH- Edu	0.006	0.001	0.008	0.008
Wald's Chi	*3456.13*		*5896.83*	
N	*1233*		*1233*	

SH denotes structural holes; D denotes density; Edu denotes educational networks; Prof denotes professional network. IVN denotes intra venture network.
Coefficients of variables number of employees, education of employees, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
Logistics regression is used for estimation.

Appendix A. Summary of the Research on New Ventures and Social Networks

Study	Type of founders' network	Dependent variable	Method
Saxenian 1990	Regional proximity	N/A	Theoretical
Brüderl and Preisendörfer 1996	Kinship	Survival, employment growth, and sales growth	Survey
Ostgaard and Birley 1996	Personal networks	Sales	Survey
Baum et al. 2000	Diversity and size of alliance network	Revenue	Survey
Jenssen and Greve 2002	Personal networks	Revenue	Survey
Jenssen and Koeing 2002	Personal networks	Information, finance	Survey
Ferrary 2003	VC's centrality, gift exchange network	N/A	Theoretical
Florin et al. 2003	Composite equally weighted measure of business network, personal network, and underwriters.	Capital raised	Archival
Elfring and Hulsink 2003	Strong and weak ties aggregated	Early performance	Case study
Witt 2004	N/a	Performance	Literature review
Lechner et al. 2006	Relational mix: reputational network, competition network, cooperative networks	Sales, time to break even	Survey
Maurer and Eber 2006	Social capital	Performance	Case study
Clarysse et al. 2007	Outside board members density	Complementary tie formation	Survey
Casper 2007	Regional proximity	Regional clusters, connections of managers	Survey
Pirolo and Presutti 2010	Customer ties	Sales, number of products developed	Survey

Appendix B. Correlation Matrix

		Mean	S.D.	1	2	3	4	5
1	SH-Edu	-27.83	5.71					
2	D-Edu	35.61	12.67	-0.16**				
3	SH-Prof	-19.22	6.33	0.17**	-0.08*			
4	D-Prof	24.43	13.08	-0.07*	0.10*	-0.19**		
5	Superimposed eigen. cent.	10.28	3.39	0.02	0.04	0.04	0.02	
6	Raised Capital	4.73	1.64	0.21***	0.11#	0.15**	0.05	0.32***

*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001; N= 6,810.*

Chapter 4:
It is a Matter of *Who* Narrates the Lines

Abstract

New ventures are at the forefront of developing IT innovations. Increasingly, new ventures turn to micro- and macro-funding social media platforms to promote their products/services and raise the necessary capital for their development. Some initial efforts have recently been made to understand how new ventures promote their products/services in funding platforms, but further insights are needed in terms of at least two important aspects.

First, while the attention has been on the content of *verbal* communication with potential investors, signals sent through *non-verbal* communications have not been considered. To address this gap, we investigate the sequence of narrators, i.e., personal (e.g., founders or employees), organizational (e.g., the official account of the venture in a funding platform), or external (e.g., news links, blog posts), who deliver promotional messages in the funding platform, as a non-verbal aspect of communication with investors. Second, social media provides a context for new ventures to promote their products/services in both macro-funding (i.e., with angels and venture capitalists as the potential audience) and micro-funding platforms (i.e., with the public micro-investors as the potential audience). While the two types of platforms require distinct ways of communication to promote the product/service, activities on one platform are observable to the main audience of the other. Therefore, studying cross-platform effects of non-verbal signals of communication can further inform new ventures about strategies to access financial capital. We investigate how the sequence of narrators in one platform affects the success of a new venture in another.

Focusing on the new ventures active in one specific industry -Big Data- i.e., Big Data ventures (BDVs), we follow the sequence of narrators in a venture's communication in one micro-investor platform, i.e., Twitter, and one macro-investor platform, i.e., AngelList. Collecting longitudinal data from 2011 to 2014, our empirical study investigates 1,213 BDVs over multiple stages of their fundraising. We examine: a) whether BDVs more successful in raising financial capital follow a converging sequence of narrators (i.e., the ideal sequence) in their social media communication; b) whether similarity to the ideal sequence (i.e., the quality of sequence) helps BDVs increase positive Word-of-Mouth (WoM) and access to financial capital; and c) whether following sequences that are appropriate for one platform leads to beneficial cross-platform spillovers. Our findings suggest that the ideal sequence of narrators varies depending on the type of innovation pursued by a BDV, i.e., incremental or radical, and that the similarity to the ideal sequence contributes to a BDV's positive WoM and financial success. Moreover, our findings provide empirical support for cross-platform effects.

Keywords: *Micro-funding, Macro-funding, Social media, Non-verbal communication signal, Sequence of narrators, Cross-platform effect, Twitter, AngelList.*

Introduction

Social media plays an important role in the success of contemporary entrepreneurial firms by providing a forum to access future stakeholders, customers, and potential investors (Fischer and Reuber 2014). Empirical evidence suggests that specifically for information technology (IT) ventures, the role of social media in promoting the business is more salient (Fischer and Reuber 2014). Since most IT ventures promote their business on social media platforms, management of Word-of-Mouth (WoM), i.e., users', customers', or followers' opinions (Gu et al. 2012), in such platforms is an important factor in explaining success (Aggarwal et al. 2012). WoM reflects interaction with external partners for IT ventures, and hence, its proper management can play an integral role in a new venture's success. Specifically, new ventures utilize communicative tactics (Fischer and Reuber 2014) as a part of their impression management strategy (Zott and Huy 2007) to maintain certainty, and thereby legitimacy, in the eyes of their audience. In doing so, modern ventures are not bound to a single communication channel, rather, they promote their product/service on multiple platforms. Specifically, while some of these platforms are intended to reach out to micro-investors in public, others are designed to attract macro-investors such as angels, venture capitalists, and larger firms (Belleflamme et al. 2014).

In spite of social media's prevalence (Rueber and Fischer 2010), as well as its distinctiveness from other channels of communication for entrepreneurial firms (Fischer and Rueber 2014), we lack understanding of the relevant communicative tactics for new ventures (Fischer and Rueber 2014). Fischer and Reuber (2014) analyze the *verbal* content of communication in social media and provide insights into the different types of content and their effects on the venture's legitimacy. In this study, we use theories of symbolic action (Zott and Huy 2007; Smith et al. 2010; Li et al. 2015) to argue that: (a) social media enables the delivery of a venture's narrative by different *narrators*; and (b) the selection of narrators can be a *non-verbal* symbolic action (i.e., "action in which the actor displays or tries to draw other people's attention to the meaning of an object or action that goes beyond the object's or action's intrinsic content or functional use" (Zott and Huy 2007, p. 70)) that affect the venture's legitimacy, and thereby access to financial resources, beyond the content of its verbal narrative.

Approaching angels and venture capitalists is not the only way to access financial resources. Instead, with the prevalence of crowdfunding, new ventures also extend their promotion activities to platforms that are more focused on micro-investors. Studying multiple platforms is therefore important. However, the general literature on WoM (Chevalier and Mayzlin 2006, Trusov et al. 2009, Burtch et al. 2013) and the literature on WoM for new ventures (Kim and Hann 2013, Mollick 2014, Thies and Wessel 2014, Lu et al. 2014, Macht and Weatherston 2014) have focused on single electronic platforms. Thus, less is known about how potentially different strategies in different platforms generate rents for new ventures, especially in the case of new IT ventures. Therefore, promotion strategies in platforms that provide communication with micro- and macro-investors should be studied simultaneously, and cross-effects of actions between the two platforms need to be understood.

We leverage signaling theories and theories of symbolic actions and theorize about non-verbal symbolic communications a new venture carries in multiple social media platforms. Focusing on new ventures active in the Big Data industry, i.e., Big Data ventures (BDVs), we follow the sequence of narrators in a venture's communication, as a form of non-verbal symbolic communication, in one micro-investor platform, i.e., Twitter, and one macro-investor platform, i.e., AngelList. Collecting longitudinal data from 2011 to 2014, our empirical study investigates 1,213 BDVs over multiple stages of their fundraising. We address the following specific research questions: 1) Do BDVs that are more successful in raising financial capital follow a converging sequence of narrators (i.e., the ideal sequence) in their social media communication (RQ1)? 2) Does similarity to the ideal sequences that are appropriate for the platform (i.e., the quality of sequence) enable BDVs to increase (a) positive WoM and (b) access to financial capital (RQ2)? and 3) Does the quality of sequence in one platform show beneficial cross-platform spillovers (RQ3)?

Theoretical Background

Impression Management

Impression management is a series of actions conducted by an organization, through which it tries to positively influence its image (Bolino and Turnley 1999; Bozeman and Kacmar 1997; Goffman 2002). Organizational impression management strategies span a wide range, broadly classified into two categories. The first category includes strategies that focus on reversing negative outcomes. These strategies can include restoring legitimacy following a controversial event (Caillouet and Allen 1996; Elsbach 1994; Elsbach and Sutton 1992; Elsbach et al. 1998; Graffin et al. 2011) or poor performance (Davidson et al., 2004), or increasing the acceptance of controversial decisions (Arndt and Bigelow 2000; Elsbach et al. 1998; Graffin et al. 2011). The second category includes strategies that focus on creating positive outcomes such as attracting minority job applicants (e.g., Avery and McKay 2006) and creating cognitive legitimacy (e.g., Nagy et al. 2012).

New ventures follow different strategies, verbal or non-verbal (e.g., Ellis et al. 2002), in order to attract much-needed financial resources (Parhankargas and Ehrlich 2014). Impression management is therefore important for new ventures (REFs). For new ventures at the early stages of development, creating legitimacy is among the most important impression management strategies (Parhankargas and Ehrlich 2014). Establishing legitimacy is important for new ventures because they face the challenges of the threats of newness and smallness (e.g., Chen et al. 2009). As relatively unknown and believed to be too-small-to-compete entities, legitimization help new ventures reduce investor uncertainty.

Although new ventures, similar to established firms, can face threats of controversial decisions and their associated negative outcomes, the salience of such threats are often at a lower level. Because of their limited public base, new ventures are rarely subject to the social scrutiny that established firms face (e.g., Parhankargas and Ehrlich 2014). Rather, their uncertain and unknown nature, in addition to their lack of access to major assets and small size, are major obstacles they face to attract financial capital from investors. Because of the salience of the threats of newness and smallness, this study focuses on legitimacy strategies in new ventures as means to reduce uncertainty for investors.

Legitimacy Strategies

"Legitimacy is a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman 1995, p. 547). Suchman (1995) offers a comprehensive classification of organizational legitimacies and discusses the context in which each type of legitimacy is meaningful. Below, we briefly discuss these classes and identify the type of legitimacy new ventures seek to established with potential investors.

The first class of organizational legitimacies discussed by Suchman (1995) is ***pragmatic legitimacy***. This type of legitimacy is called pragmatic because it is based on self-interest calculations in an organization's specific contract. A focal organization is deemed legitimate if it is believed to benefit, or considered to have the potential to benefit, its customers or partners in the context of a specific contract. This type of legitimacy is *evaluative* since it rests on the positive outcomes an organization provides, but is *subjective,* because the positive outcomes for the subjects of a specific contract are considered.

A second class of legitimacy is referred to as ***normative legitimacy*** (Suchman 1995). This type of legitimacy is also evaluative, but the evaluation is not done by the immediate trade parties of an organization, or with relation to a certain contract. Rather, the evaluation is made by observers based on the organization's general conformity to socially accepted norms, values, and beliefs. Therefore, although this second type of legitimacy is also evaluative, it is more objective compared to the pragmatic legitimacy.

A third class of legitimacy is ***cognitive legitimacy***, also referred to as ***taken-for-granted legitimacy*** (Suchman 1995). This class of legitimacy is not evaluative; that is, an organization is perceived legitimate if its existence, whether with positive, negative, or neutral outcomes, is *justified* in a social system.

The above three classes of organizational legitimacies have clear distinctions. While the first two are evaluative, the third one is not. Also, pragmatic and normative legitimacy differ in the agency of the evaluator. In the pragmatic legitimacy, the evaluator has some contractual ties with the organization. However, in the normative legitimacy, the evaluator is not tied to the organization with a specific contract[25] (Suchman 1995). Based on these differences, we believe normative legitimacy is the most salient type of legitimacy relevant to new ventures because potential investors often evaluate a venture and do so while they are not necessarily focused on an existing contract. Investors choose ventures that are deemed to be successful in a broad

25Although in the future, there might be a specific contract, but the legitimacy is not subject to, or limited to it. Rather, the evaluation is made in a broader sense and with regards to the general conduct of the organization.

market (e.g., MacMillan et al. 1986), and since the notion of market success is socially-constructed through what is socially accepted as successful and prosperous for a firm (Zott and Huy 2007), establishing legitimacy by new ventures through social media is mainly normative.

Normative legitimacy can be established through four broad strategies. First and foremost, ***consequential legitimacy*** is highlighted as a type of legitimacy that is gained when an organization is believed to produce desirable outcomes for its customers (Suchman 1995). For example, in the literature about new ventures, focus on legitimizing through quality is highlighted as a key activity (Fischer and Rueben 2014). High quality products and services are met with satisfied customers and therefore increased market success. As a result, emphasizing quality is a way to construct consequential legitimacy. Two other related strategies for establishing normative legitimacy are ***procedural legitimacy***, where an organization signals superiority by following desirable organizational procedures, and ***structural legitimacy,*** where the superiority is signaled through adopting well-accepted organizational structures. Finally, ***personal legitimacy*** rests on the competence and passion (Chen et al. 2009) shown by leaders, founders, and innovators of a new venture (Suchman 1995).

Pursuing Normative Legitimacy in Social Media: Symbolic Communication

The existing literature suggests that organizations follow a set of symbolic actions, i.e., "action in which the actor displays or tries to draw other people's attention to the meaning of an object or action that goes beyond the object's or action's intrinsic content or functional use" (Zott and Huy 2007, p. 70), to establish normative legitimacy (Zott and Huy 2007). Specifically, ***symbolic communication*** with the public and/or potential investors is deemed an effective means for conducting these symbolic actions (e.g., Aldrich and Fiol 1994; Golant and Sillince 2007). Most notably, Lounsbury and Glynn (2001) suggest that new ventures must use *stories*, as a type of symbolic communication, to distinguish themselves and reduce the uncertainties that may exist with regards to their potential for success. For example, Martens et al. (2007) found that ventures emphasizing a pioneering nature and a track record of supporting it in their reports/proposals to investors are more successful with regards to their valuation premiums at initial public offering (IPO). Similarly, Zott and Huy (2007) highlight the role of emphasizing personal credibility, capability for professional organizing, quality of relationships with partners, and organizational achievements in a venture's narrative to the public, as pertinent to its access to external resources.

For new ventures, social media is an emerging channel for symbolic communications (e.g., Fischer and Rueben 2014). Focusing on verbal cues in communication, Fischer and Reuber (2014) found that emphasizing quality, a relational orientation, distinctiveness, and positive affect in the *content* of venture's twitter posts is most likely to positively affect investors' perception of the venture's quality or distinctiveness.

Although content is a major part of communication, the agency of narrator, i.e., *who* narrates the content, is also part of the signal that the audience receives. We suggest that choosing agency of the narrator can also be a symbolic action by a new venture. For example, both a founder and a non-affiliated blogger can provide a similar narrative, signaling quality of a venture's innovation. Specifically, social media, such as Twitter, allows a new venture to cast its narrative by either source. However, the meaning of a narrative being told by the venture's founder can be very different from one that is told by a non-affiliated blogger. A founder's signaling of quality might be perceived as bragging (e.g., Chan et al. 2009), whereas a non-affiliated affirmation of quality might not be seen as such. Supporting the importance of non-verbal cues, the extant literature suggests that symbolic actions can also be carried in a non-verbal fashion (Zott and

Huy 2007), although such non-verbal cues in communication are under-studied. Taking part in certification contests (Rao 1994) or displaying artifacts in offices (Clarke 2011) are examples of non-verbal symbolic actions documented in the existing literature.

Therefore, while the existing literature about the symbolic communication in social media (Fischer and Rueben 2014) has focused on the verbal aspects (by focusing on the content of narrative communicated), this paper focuses on non-verbal cues in the communication, by considering the agency of narrator.[26] Below, we discuss the social media-enabled capability to select the narrator of a message and the normative legitimacy strategy that each narrator enacts.

Narrators in Symbolic Communication

In the offline world, *Initial Public Offering* (IPO) prospectuses are exemplar mediums through which innovators present their *formal* communications to investors (Martens et al. 2007). These formal narratives are stories conveyed at a single point of time (Lounsbury and Glynn 2001) where any interested audience can access it (Fischer and Rueben 2014). Contrary to these formal communications are symbolic communications that are signals embedded in interpersonal interactions conveyed across time and accessible only to those who are present at the point of interaction (Fischer and Rueben 2014). In both formal and symbolic communications, there is a limited variability in the agency of narrator. IPO prospectuses are often written by founders, and interpersonal interactions with stakeholders are usually carried by a venture's employees, if not by the founders themselves.

However, symbolic communications carried in social media show distinct attributes. Unlike offline symbolic communications, those enabled by social media have a broad audience reach.

26In this study, we control for the valence of the content, but since the previous literature has hypothesized and empirically validated the effects of content, we do not formally hypothesize about it.

More importantly, social media-enabled symbolic communications can be narrated by different agents. Social media allows transferring of a message by providing a web link to a blog or news report regarding the venture. It also allows the narrative to be broadcasted by organizational or personal (e.g., founders' or employees' account) aliases. For example, in Twitter, a new venture can post tweets promoting the venture's business through four narrators. First, a message can be posted by the personal Twitter account of founders or employees. An alternative to this approach is posting content through the official Twitter account of the venture. The third option is providing a link to a blog post or news article about the venture. Fourth, the venture can re-tweet the content that the public has created about the venture. Although social media platforms are different with regards to different narrators that can convey symbolic messages, they share the ability to allow different narrators to carry conversation with the same audience.

At a broad level, social media enables narrative to be told by organizational, personal, and external agents. Below, we discuss the type of normative legitimacy that each of these agents affirm. Well-established firms often communicate through an organizational alias in social media. For example, news about different products of Sony are broadcasted by Sony's official Twitter account directly to its followers. Therefore, broadcasting with organizational alias is an institutionally accepted norm. When a new venture broadcasts a message by its official venture alias, a conformity to well-established norms is maintained. To outsiders, conformity to the broadcasting behavior of well-established firms signals presence of procedures and structures that match those of stable organizations. Therefore, we suggest that broadcasting with a venture alias affirms procedural and structural legitimacy.

On the contrary, a part of new ventures' news is communicated by founders or employees (Fischer and Reuber 2014), a case that rarely happens for well-established firms. Although this behavior does not enhance procedural or structural legitimacy, it may affirm personal legitimacy. Specifically, Chen et al. (2009) suggest that showing passion by founders and employees is a strategy to improve personal legitimacy. Passion shows confidence in a new venture's innovation and thereby can signal the positive perceptions of founders and employees about what they do. When a founder or employee of a new venture personally broadcasts a message, it signals a level of enthusiasm, reflecting on personal passion. Thus, we suggest that broadcasting through a personal alias affirms personal legitimacy.

Finally, broadcasting a message through external agents, e.g., news agencies and bloggers, can signal non-verbal consequential legitimacy. Specifically, external agents' talking about a new venture suggests how well-accepted the new venture is in the social system in which it operates. Therefore, aside from the content of the message, narration of news by others suggest that the venture has been influential enough to spark conversation in the outside world, hinting at its consequential legitimacy. Public approval is regarded as a mode of consequential legitimacy for firms (Pollock and Rindova 2003).

In viewing non-verbal cues of symbolic communication, we take into account the processual nature of symbolic communications. Elaborating on the nature of symbolic communications, Fischer and Reuber (2014) note that such communications are not issued at a single point of time and rather "consist of multiple messages conveyed over a span of time" and are "a collage of individual signals, rather than a unified and integrated narrative" (p. 569). In spite of their theoretical acknowledgement of the processual nature of symbolic communication, Fischer and Rueben's empirical treatment of communication in social media is through a variance approach. Focusing on the non-verbal cues in symbolic communication, this study considers the *sequence* of narrators conveying a venture's message as its symbolic action, In other words, we view a new venture's non-verbal symbolic communication as the sequence of narrators it chooses to deliver messages to its audience. A process view enables us to follow a BDV's communication through time, conceptualizing symbolic communication by including the time element. Given the lack of studies on non-verbal communication cues in social media, this study adopts an inductive approach to understand symbolic communications that suit new ventures. In doing so, we are guided by the signaling theory to explain how different symbolic communications can affect the new venture's success in accessing financial capital. Figure 1 summarizes the above discussion on legitimacy strategies for new ventures and the relevant non-verbal tactics in social media.

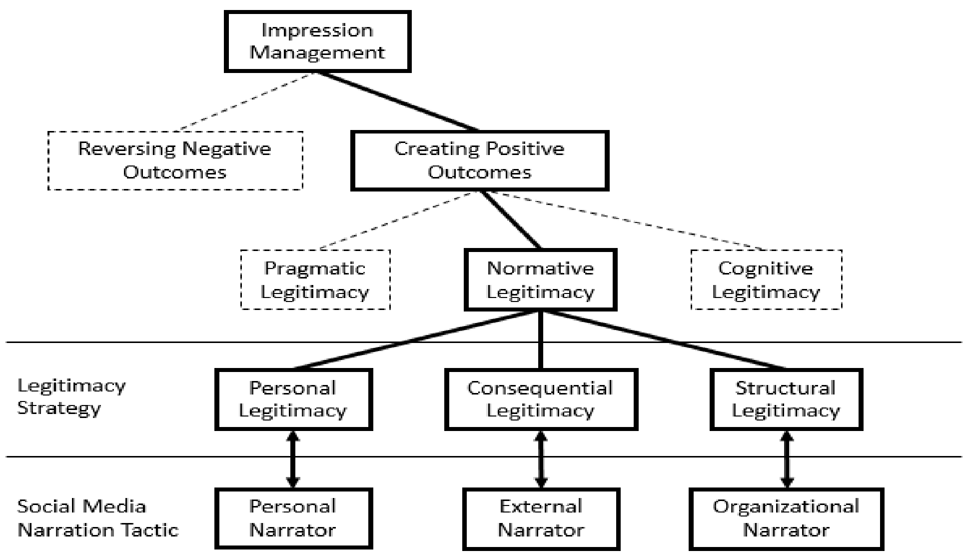


Figure 1. A Theoretical View of Impression Management in New Ventures

Signaling Theory

Signaling theory is concerned with reducing information asymmetry between two parties (Connelly et al. 2011). Information asymmetry is defined as a situation when two parties involved in an economic transaction have access to two different sources of information related to the transaction (Spence 2002). Tenets of the signaling theory suggest that when one party is at information disadvantage (i.e., faces uncertainty), peripheral information vis-à-vis the focal transaction is used as surrogate information (Boulding and Kirmani 2003). For example, a more recent study shows how CEOs signal the unobservable quality of their firms to potential investors via the observable quality of their financial statements (Zhang and Wiersema, 2009).

For entrepreneurial firms at the early stages of developing their product/service, when the initial capital needed to establish the business is raised, potential investors face uncertainty. Since the final product/service is far from being experienced and evaluated by investors, they must rely on other informational cues to trust and invest (Elitzur and Gavious, 2003).

We suggest that non-verbal symbolic actions are organizational signals that can be used by potential investors to reduce the uncertainty. Therefore, the extent of a new venture's success to persuade potential investors depends on the extent to which the new venture's symbolic action reduces the investors' uncertainty. New ventures are not homogeneous with regards to the type of uncertainty their investors face. Specifically depending on their innovative strategy, new ventures and their investors face different kinds of uncertainties and require different symbolic actions.

Theoretical Development

Radical vs. Incremental Innovations and Investor Uncertainties

Innovation is at the heart of entrepreneurial firms at the early stages of development (Zott and Amit 2007). Absent traditional firm resources, such as liquidity, reputation, and extensive human capital, innovation is the main source of value for these ventures (Zott and Amit 2007). To develop, grow, and stabilize, new ventures need to attract capital from venture capitalists and angels, mainly through a persuasive innovation that shows the potential and promise of business success (Timmons and Bygrave 1986). New ventures follow different strategies in developing their innovations. Some focus on radical novelty, where product/service is a clear and often risky departure from the existing technology (Ettlie et al. 1984). Others pursue incremental innovations where the focus is on improvements, modifications, or re-configuration of existing technology (Ettlie et al. 1984).

Entrepreneurial firms face two major liabilities: liability of smallness and liability of newness (Rosenbusch et al. 2011). While the first concerns the limited size of new ventures and their ability to compete with established firms, liability of newness concerns the unknown nature of the firm's product/service and its reception by customers (Rosenbusch et al. 2011). These two major liabilities are the sources of concern for potential investors, and their limited access to information about the firm's ability to overcome the threats of these liabilities creates uncertainties. While the two liabilities to some extent exist in all new ventures, the salience of them can be different depending on the innovative strategy they pursue.

We contend that for radical innovations, the liability of newness is more pronounced than the liability of smallness. Because of the breakthrough nature of innovation, and thus lack of benchmarks, evaluating the reception of a radical innovation in the market is hard for investors. However, due to their uniqueness, less competition is expected to come from established firms; thereby, the liability of smallness is reduced. On the contrary, liability of smallness is more pronounced for new ventures pursuing incremental innovations. Since an incremental innovation is an extension to an already-existing product/service, evaluating market reception is less cumbersome for potential investors. However, the presence of established firms, as competitors with the pre-modified version of the service/product, increases the likelihood of head-to-head competition; thus, the threat of smallness becomes more important. In other words, investors' uncertainties lie in whether or not the new venture has the required structure to compete with mature firms.

Symbolic Actions: Radical vs. Incremental Innovations

We suggest that different symbolic actions that establish organizational legitimacy are required to overcome uncertainties about smallness and newness. Specifically, we contend that establishing procedural and structural legitimacies suit uncertainties that arise due to the liabilities of smallness. The more a new venture is capable of showing its conformity to procedural and structural attributes of established firms, the more its investors are convinced that the venture has the maturity to compete with larger firms. On the contrary, establishing personal legitimacy can be more effective for reducing uncertainties due to newness. Absent a track-record, investors rely on the competence of innovators to evaluate the promise of an innovation (Suchman 1995; Chen et al. 2009).

Therefore, as a new venture establishes personal legitimacy, the uncertainties about newness subside. Finally, consequential legitimacy is suitable for uncertainties that arise due to both smallness and newness of new ventures. Specifically, external affirmation can signal market enthusiasm and therefore positive reception of a future product/service. Hence, it can address the liability of newness. On the other hand, external affirmation of quality can signal a favorable market attention, indicating a capability to attract market attention in the presence of competition. Therefore, for new ventures pursuing a radical innovation, higher focus on personal and consequential legitimacy signals are more effective, whereas for those pursuing incremental innovations, focus on structural, procedural, and consequential legitimacy signals can be more beneficial. Figure 2 represents a summary of the discussion thus far:

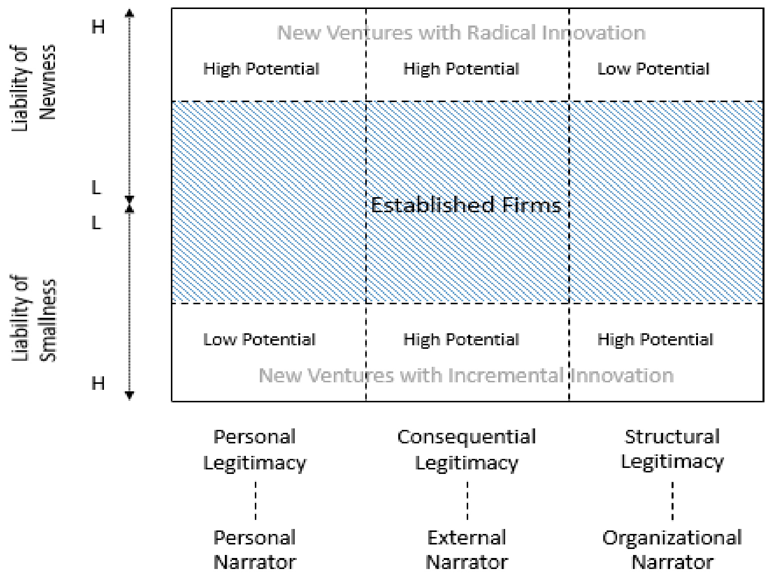


Figure 2. An Overview of Legitimacy Strategies and Tactics Suitable for New Ventures Pursuing Radical vs. Incremental Innovations

Although the existing literature informs us about the different signals required for different innovative strategies, the *sequence* of these signals cannot be hypothesized *a priori*. Specifically, symbolic actions are carried out over time and thereby, hypothesizing about isolated signals is theoretically immature. Due to lack of existing literature with regards to the sequence in which symbolic action should be carried, we adopt an inductive approach and study the sequence of narrators in organizational communication at social media. Given the difference between innovative strategies with regards to the signals required to alleviate investor uncertainties, we propose that:

P1: The ideal sequence of signals sent through selection of narrators differ for radical and incremental strategies of innovation.

Also, since selection of narrators can help to establish legitimacy and such legitimacy reduces investor uncertainties, and given the proposed difference in ideal sequence of signals for ventures pursuing radical and incremental innovations, we propose that:

P2: Ventures that follow a sequence of signals closer to the ideal sequence that suits their innovative strategy, i.e., ventures with higher sequence quality, become more successful in attracting investors.

WoM as a Mediating Mechanism

At the receiving end of communication messages sent by new ventures is the audience. In the social media context, in addition to the new venture itself, the audience can also express its sentiment and opinion (i.e., WoM) about the new venture. A successful symbolic communication by a new venture can be evidenced by a positive reception from the audience. Successful persuasion of audience can lead to increasing discussions about the venture (increase volume of WoM) and also can lead to expressing of positive sentiments about it (increase in valence of WoM). Therefore, symbolic communications, and specifically the sequence of narrators, can affect WoM. High volume of WoM and its positivity can then create a positive social disposition towards the venture and encourage investment. The existing literature in other contexts shows that volume (e.g., Chevalier and Mayzlin 2006) and positive sentiments about a business (e.g., Liu 2006) positively affect the financial gains. Therefore, we propose that:

P3: Ventures that follow a sequence of signals more similar to the ideal sequence that suits their innovative strategy, i.e., ventures with higher sequence quality, become more successful in attracting investors by increasing the volume and positive valence of WoM in the social media.

In the age of crowdfunding and importance of micro-investors, new ventures rarely rely only on social media that enables interactions with angels and venture capitalists (Agarwal 2011). Rather, in an effort to access micro-investors, more general social media platforms, such as Twitter (Fischer and Reuber 2014), are also used to pursue symbolic communication. Therefore, symbolic communications can be carried out in the multiple platforms. Since communications in one platform are visible for the audience at the other platform, it is logical to assume that communication in one platform can have an effect on investors who are the main audience of the other platform. We are unaware of studies that have examined the cross-effect of symbolic actions in different social media platforms. Therefore, we propose that:

> P4: The effect of narrator sequence quality in one platform on access to financial resources is also mediated through increase in the volume and positive valence of WoM in the other platform.

Figure 3 presents an overview of our research model that guides us to study the effect of narrator sequence quality on the success of BDVs in a round of fundraising.

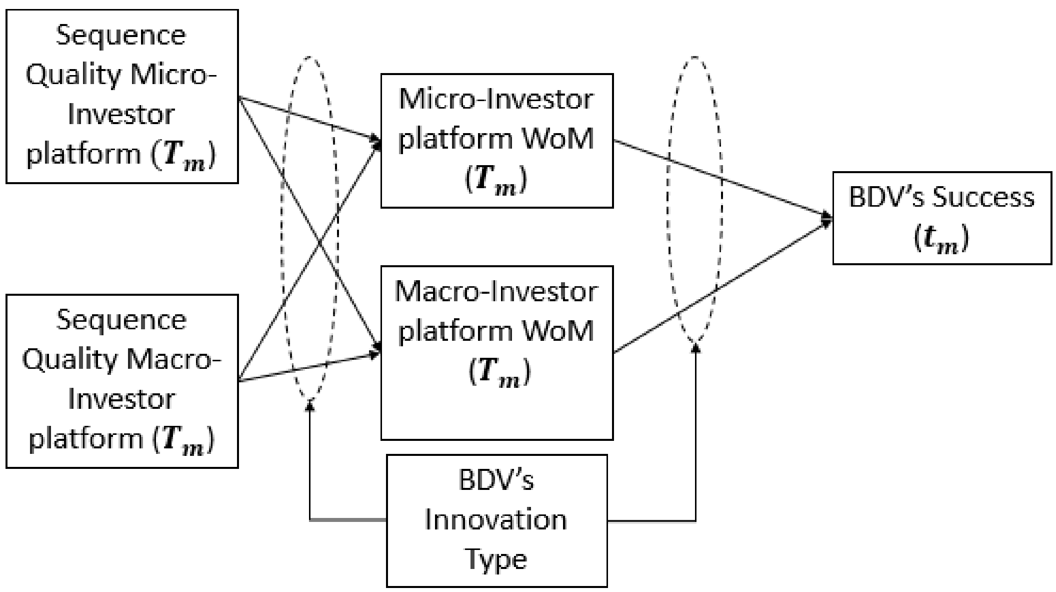


Figure 3. Research Model

Methods

This essay utilizes a field study and mixes qualitative approaches used to identify different non-verbal symbolic actions in a venture's communications, with quantitative approaches used to study the role that quality of the symbolic actions plays in the venture's access to financial resources. This research focuses on BDVs active on AngelList.com, a venture-funding website that offers a platform to new ventures to connect to other ventures and gain access to investors. Big Data is a growing area in the IT industry with active emergence of new ventures (Dhar

2013). Following the tradition of focusing on the high-tech industry in entrepreneurial studies (e.g., Baron and Hannan 2002; Colombo and Grilli 2010; Bertoni et al. 2011; Anderson and Xiao 2016), we select Big Data as a niche high-tech context. A total of 1,213 BDVs were followed from January 1, 2011 until December 29, 2014, resulting in 4,113 venture-round observations. These ventures are self-identified as active in the Big Data context. An average BDV in our sample has raised $4.67 million and has 3.42 co-founders and 11.88 employees. The website assigns a profile page to each BDV where information such as names and links to personal pages of founders, employees, investors, and followers of the BDV are identified. Additionally, information regarding different rounds of capital-raising, amount raised, and contributing investors in each round is provided. Finally, the profile page includes a section where the BDV's innovation is described and introduced. Using a Python-based web-crawler, the mentioned information about each BDV is crawled and used as the main source of information. This information is then supplied by accessing the LinkedIn profile of founders, employees, and co-founders, where information about professional background, academic background, and the friend list of each individual is obtained.

Data

The study focuses on Twitter as a social-media platform with high presence of micro-investors and AngelList.com as a platform highly directed at macro-investors. We treat the tweets created by the venture's official Twitter account (including those with links to other sources, or re-tweets of others' mentioning of the venture) and those created by the founders or employees of the venture, mentioning the venture's official account, as the venture's communication in Twitter. To capture the communications in the AngelList, the content posted by the venture's "Activity" page is tracked. Specifically, the content posted by the page itself or comments inserted by founders or employees of the venture are treated as the venture's communication in AngelList. The narrator of each piece of communication, its content, and the time at which the communication message is created are stored in a spreadsheet. In Twitter, the message of the communication can be narrated by: a) venture's official Twitter account (venture alias); b) venture's founder or employee (personal alias); c) external piece of news or blog post (news); or d) followers (through re-tweets; followers). In AngelList, the message of the communication can be narrated by: a) venture's official AngelList account (venture alias); b) venture's founder or employee (through personal comments on the activity page; personal alias); c) external piece of news or blog post (in the "press" section of the activity page; news).

In order to test the propositions, we focus on the periods between two fundraising events and panel the new ventures in our sample based on that time stamp. In each period, a sequence of narrators is identified for each venture in each platform. Each sequence represents the non-verbal symbolic action carried by a new venture in a given platform. For example, venture alias→news→personal alias→followers can be the narrator sequence of a venture in its Twitter in a given period of fundraising.

Measures

Quality of non-verbal symbolic communications

In order to calculate the quality of non-verbal symbolic communication for each venture in each platform at each round of fundraising, we calculate the distance between the narrator sequence of the venture's communication in a given platform at time t from the sequences belonging to the top 10 percent ventures with highest raised capital. We assume that top performing ventures follow a desirable sequence; therefore, further distance from such desirable sequences implies lower quality of the non-verbal symbolic action followed by a venture.

The distance between two sequences is computed as the least effort needed to transform one sequence to another, through insertion, deletion and substitution of events. In our sequence, each narrator type (e.g., venture alias, link) selected for delivering a message is treated as an "event." Before computing the minimum transformation cost, the cost of one insertion, deletion, and substitution needs to be identified. For any one process of transforming one sequence into another, the numbers of insertion, deletion, and substitution operations that are needed for the transformation, and the costs associated with one operation of each type, are then used to compute the cost associated with that transformation process. For a given pair of sequences, numerous alternative transformation process can be identified, each with an associated transformation cost. The lowest of these transformation costs is then considered as the distance between the two sequences. Since the number of alternative transformation processes increases as each of the sequences becomes longer in terms of number of events, and numerous pairs of sequences may be involved in a project, automating the computation of the lowest transformation cost is important[27]. The optimal matching algorithm (Abbott 1995) has led to such automation through optimal matching packages in statistical software, including *STATA*.

In order to ensure that the cost of transforming sequence A into sequence B is the same as the cost of transforming B into A, insertion and deletion costs need to be kept equal. We set deletion and insertion costs to 0.5. We assigned cost of 0.6 for substitution of narrators, because the cost for substitution of events should be smaller than the sum of insertion and deletion (here, 0.5+0.5 =1). Optimal matching through *STATA*'s *SQ* package was then used to compute inter-sequence distances. For each venture at time t, the average distance from the sequences of top 10

[27]To make the inter-sequence distances less sensitive to the size of the two sequence, the inter-sequence distances are divided by the length of the longer of the two sequences.

percent ventures in Twitter and AngelList is calculated, and the inverse ratio of the average distances is used as the quality of non-verbal symbolic action in the social media platforms.

WoM

Volume of WoM in Twitter for each BDV is calculated by counting the tweets mentioning the BDV, posted by non-affiliated individuals. The valence of these tweets are evaluated following Mudambi and Schuff (2010), and the degree of positivity is used as the measure of the WoM valence. Volume of WoM in AngelList is calculated by counting comments made by non-affiliated followers in the activity page. The valence of these comments are calculated similar to the calculations in the case of Tweeter tweets.

Innovation strategy

In order to determine the innovation strategy (radical vs. incremental), we conducted a text analysis of the product description section of the BDV's profile in the AngelList website, supplemented with blog and news reports about the BDV's innovation, obtained from Lexis-Nexis. We believe a BDV's innovation type can be understood by reviewing the product description section of the BDV's webpage because that section is the medium through which the product is introduced and its potential superiorities to competing products are explained. Further, news pieces and blog posts provide outsiders' view of the BDV's innovation. The text-mining module of R (tm) was used to analyze the product description section of each BDV's profile, as well as related news pieces and blog posts. In order to do so, first, a set of words associated with radical and incremental innovations was compiled using the existing literature on organizational innovations. We searched Google Scholar for articles that contained the terms: incremental innovation, and radical innovation. Over 12,100 articles were identified, and the HTML versions of these articles were combined to form a corpus. This corpus was text-mined to extract sentences that did not include any of the keywords “radical innovation” or “incremental innovation” with the exception of sentences that were adjacent to the sentences containing these words (i.e., one sentence before and one sentence after the sentence containing the keyword). Then, the sentences containing the mentioned keywords and their adjacent sentences were analyzed to form a network of words that are closely associated with them. For example, the words “original,” “breakthrough,” “pioneering,” and “groundbreaking” had the highest frequency of occurring when the word “radical innovation” was discussed in the corpus of articles. Also, the words “revise,” “extend,” “amend,” “combine,” “re-configure,” and “modify” were adjacent to the word “incremental innovation.” The adjacent words were then processed to eliminate the ones that are irrelevant to the concepts of incremental and radical innovations. Then, a library of refined word for each type of innovation was used to analyze the product description section of each BDV in the sample. The frequencies of words associated with radical and incremental innovations in the product description corpus of each BDV are calculated. The ratio of associated words to the total number of words in the text is calculated to measure emphasis on a radical vs incremental approach. The two ratios are then compared with a z-test to determine the category of innovation; the significantly larger ratio determines the category of radical or incremental innovation. Observations with insignificant z-test are dropped from further analysis.

Raised capital

The information about the raised capital in each round was collected from AngelList.com’s profile of the BDVs[28]. From the conception to business planning, product development, commercialization, operationalization, expansion, and eventually public offering, new ventures

28Appendix A presents the correlation matrix for main variables in the study.

raise funds from different resources (e.g., Cumming 2007). 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 BDV raises external funding at multiple rounds in the same stage of development. Therefore, a new venture might have two or three rounds of seeding. In our operationalization of a fundraising period, we focus on each round of fundraising and use the raised capital in that round as the dependent variable. Then, we control for the stage at which the capital is raised.

Controls

Although our focus is on non-verbal symbolic actions, we believe that the content of a message communicated by the BDV to its audience influences the raised capital. Specifically, Fischer and Reuber (2014) show that the valence of messages communicated can reduce the uncertainty for investors. Therefore, a similar algorithm used in evaluating the valence of social media WoM is used to estimate the **valence of messages communicated by a BDV** at time t.

As mentioned above, we control for the **stage of development** where the funding is raised. We do so because early and late stages of fundraising are different in terms of the funding providers,[29] as well as the amount of the capital needed.[30] To best capture the effect of the fundraising stage, for each stage of development (e.g., seeding, stage A, etc.), we specify a variable, the value of which indicates the number of fundraising rounds a new venture has completed in that stage, prior to the current round. Therefore, for BDVs with their first round of fundraising, the value of seeding, stage A, stage B, and stage B variables is all set at 0. If a venture has had two rounds of fundraising at the seeding stage, and the current round is its

[29]For example, angels contribute more in the early stages of the development, whereas venture capitalists do so in the later stages close to the initial public offering (IPO).

[30]Usually, the financial capital needed in the early stages of development are smaller than the capital needed in the later stages.

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.

Also, we control for the **number of years** since a BDV has been established as the time elapsed since establishment can have an effect on accessible resources, financially and intellectually. We control for the **location dummy**, measured at the city level, whether or not the venture identifies itself as a **business-to-business** or business-to-customer (identified by tags reported in AngelList.com), and the **technological scope** dummies, which represent the area of focus in the Big Data context (identified by tags reported in AngelList.com; can be analytics, security, or infrastructural). Moreover, the **number of employees** (including co-founders) in the fundraising period of interest, and average of employees' (including co-founders) value of **education** are controlled for.

Analysis

We start our inductive approach with understanding the narrator sequences employed in Twitter and AngelList[31]. We start our inquiry by striving to find out if more successful BDVs adopt a certain sequence of narrators when communicating with their audience. In order to so, we rank the BDVs in our sample based on their raised capital at each round. Given our focus on radical and incremental innovations, we first divide our sample based on the innovation strategy and carry out the analysis in each sub-sample. We treat the top 10% BDVs as successful BDVs and investigate the similarity of their sequences. If top-performing BDVs follow similar sequences, it can be an indicator for the existence of an ideal sequence. On the other hand, if the sequences followed by top-performing BDVs are diverging, it can imply that narrator sequences might not be understood within a singular underlying ideal theme.

[31]Appendix B presents examples of promoting events in Twitter and AngelList narrated by different narrators.

To assess the presence of an underlying ideal sequence, we compare the average distance that a top-performing BDV's sequence has from the other top-performing BDVs' sequences to the distance it has with sequences of BDVs in the rest of the sample. For each BDV-period observation ranked in top 10% (with regards to its raised capital), the sum of inter-sequence distances from all other BDV-periods in top 10%, as well as the sum of inter-sequence distances from the BDVs in the rest of the sample, is estimate. Then, and from the two estimates, the average distance from the top 10% BDVs and the average distance from the BDVs in the rest of the sample are calculated. If this calculated statistics is significantly different from zero, a meaningful difference between sequences of top 10% observations and the rest of the sample is implied. We conduct a series of Z-tests to investigate this hypothesis. Results of the z-test show (for radical Twitter (z-value: 3.52), for incremental Twitter (z-value: 3.22), for radical AnagelList (z-value: 3.46), for incremental AngelList (z-value: 3.43)) that we can reject the null hypothesis that the sequences of top-performing BDVs are similar to the rest of the sample. This implies that a converging underlying sequence exists for the top-performing BDVs. We call this sequence an *ideal sequence*. In order to identify this underlying sequence, we focus on the centroid sequence of the top-performing BDVs. A centroid sequence in a set of sequences is the one that has the lowest distance from all of the other sequences in the set (Abbott 1995).

Below, we discuss the four centroid sequences in the set of top-performing BDVs, for both Twitter and AngelList with radical and incremental innovations. The following is the centroid sequence in Twitter for BDVs pursuing a radical innovation:

personal alias → *news* → *venture alias* → *follower* → *news* → *personal alias* → *follower* → *personal alias*

For simplicity, we have merged narrators of the same type in cases that the same type of narrator is chosen for two consecutive messages[32]. The following is the centroid sequence in Twitter for BDVs pursing an incremental innovation:

venture alias → *news* → *personal alias* → *follower* → *news* → *venture alias* → *news* → *venture alias*

The following is the centroid sequence in AngelList for BDVs pursuing a radical innovation:

personal alias → *news* → *personal alias* → *news*

And finally, the following is the centroid sequence in AngelList for BDVs pursuing an incremental innovation:

news → *venture alias* → *news*

The centroids from top-performing BDVs reveal few important patterns. First, in all four centroids a degree of alternating between internal (i.e., those messages cast by the venture or founders/employees) and external narration (i.e., those messages cast by a news link or re-tweets of external followers). This preferred alternation between the external and internal narrators is consistent with the previous research findings that suggest too much emphasis on self-promotion can prove harmful (Parhankargas and Ehrlich 2014).

Second, and for radical innovations, with their greater degree of uncertainty, more emphasis, especially in beginning and concluding phases of promotion where effects of promotion are shown to be more influential (e.g., Lu et al. 2014), on establishing legitimacy through passion (personal legitimacy) is observed; whereas, for incremental innovations, more emphasis on structural legitimacy is observed when self-promotion is concerned. This is consistent with our prior discussion about the salience of newness and smallness liabilities for radical and incremental innovations, respectively. In the critical phases of communication, and when

[32]For example a hypothetical sequence of "news→follower→follower→follower→personal alias" is presented as "news→follower→personal alias".

establishing legitimacy through internal narrators is concerned, personal narration and a focus on the narrator's passion is followed by the top-performing BDVs. This can help a BDV reduce the uncertainties about liability of newness as the more salient liability when a radical innovation is pursued. On the contrary, BDVs pursuing an incremental innovation focus on structural legitimacy (through venture alias communications) in order to reduce uncertainties regarding the smallness liabilities.

Third, an observed difference between the non-verbal symbolic actions carried in platforms focused on micro- and macro-investors is the internal or external agency of the narrators. For platforms focusing on micro-investors (e.g., Twitter), internal narrators (venture or personal alias) are chosen, whereas for platforms focusing on macro-investors (e.g., AngelList), external narrators are selected. The concluding phases of fundraising campaigns are important because more activities with regards to the investments happen in these phases (Lu et al. 2014). Our findings reveal that for macro-investors, with their explicit processes to evaluate new ventures (e.g., MacMillan et al. 1986), external affirmation becomes more important. It is likely to assume that personal legitimacy, and vetting the structural soundness of a new venture is evaluated earlier in the process of making a judgment about an investment. Therefore, external affirmation about the potential of a new venture can fortify the already-gathered information about the new venture and its founders. To the contrary, micro-investors follow less-elaborate processes to land a decision about making an investment in a new venture (Gerber and Hui 2013). Therefore, it is logical to assume that micro-investors make more instant decisions putting more weight on the more recent activities by the new venture. A direct communication between the venture and an investor (instead of making it by the proxy of news links or blog posts) can be a more direct and effective approach.

In the next step, we evaluate the effect that the quality of sequence of narrators have on the raised capital by BDVs. Since our calculation of the sequence quality involved reviewing the top 10% performing BDVs, we drop the top 10% and bottom 10% observation from further analysis. In order to investigate the research propositions, we construct a panel where each BDV is observed in each round of fundraising (i.e., the BDVs are paneled over the rounds of fundraising). This resulted in 4,113 venture-round observations. We split the sample to BDVs pursuing radical and incremental innovations, and the statistical models are run within each sub-sample. For all the models, and due to the panel structure of the data, the models are processed using a generalized least squares (GLS) estimation with panel-specific corrections for first-order auto-correlation and heteroskedasticity. Specifically, we run three models, one with WoM at the Twitter as the dependent variable, while considering the noted controls in addition to the quality of narrator sequence at both Twitter and AngelList, their interactions, and controlling for the effect of WoM in AngelList. The second utilizes WoM at AngelList as the dependent variable, while considering the noted controls in addition to the quality of narrator sequence at both Twitter and AngelList, their interactions, and controlling for the effect of WoM in Twitter. The third model utilizes raised capital as the dependent variable, while considering the noted controls in addition to the quality of narrator sequence at both Twitter and AngelList, their interactions, WoM in Twitter and AngelList, as well as their interactions. The interaction terms are analyzed in a hierarchical fashion, after the direct effect models are examined. Table 1 presents the results, with WoM in Twitter and AngelList as the dependent variables.

The direct effect models for BDVs pursuing incremental and radical innovations show that the quality of narrator sequence in one platform is positively and significantly associated with more positive sentiments in that platform (sequence quality in Twitter→Twitter WoM; sequence quality in AngelList→AngelList WoM). Fruther, the positivity of WoM sentiment in one platform is also positively and significantly influenced by the quality of sequence in the other platform (sequence quality in AngelList→Twitter WoM; sequence quality in Twitter→AngelList WoM). This provides evidence that the legitimacy-building actions in one platform spill over in other social media platforms. To best of our knowledge, this study is the first to document such cross-platform effects. Finally, the results of the direct-effect models indicate that in BDVs pursuing radical and incremental innovations, positive sentiment of WoM in one platform enhances the positivity of another platform's WoM (Twitter WoM→AngelList WoM; AngelList WoM→Twitter WoM).

The interactions model shows differences between BDVs pursuing radical and incremental innovations. Specifically, the quality of sequence in the two platforms become complementary only when a radical innovation is pursued. Our results show a significant and positive interaction between quality of sequence in the two platforms when effects on the platform WoM are concerned (sequence quality in Twitter* sequence quality in AngelList→Twitter WoM; sequence quality in Twitter* sequence quality in AngelList→AngelList WoM). These results may imply that investors considering an investment in radical innovations expand their search for legitimacy cues beyond one platform, and therefore the quality of non-verbal cues in one platform enhances the effect of the quality of sequence in the other platform. If investors limit their search for legitimacy cues to only one platform, then the joint effect of quality should not significantly affect the WoM. This is the case for BDVs pursuing an incremental innovation. The findings may imply that investors considering investment in ventures pursuing incremental innovations face a lesser degree of uncertainty, and thus additional cues from multiple platforms might not be considered. Since the investors are more likely to consider cues from one platform, cues from the other do not make any additional value.

---Insert Table 1 here---

Table 2 presents the result when the raised capital is the dependent variable. Results of the direct effects model show that the quality of sequence in both platforms remain significantly and positively associated with the raised capital, in spite of the significant and positive association between the positivity of the sentiment of WoM in both platforms and the raised capital. Taken together, these results imply a partial mediation. Also, the results from the interaction model show that the positivity of sentiments from WoM in Twitter and AngelList are complementary in the case of radical innovations but not for the incremental innovations[33].

---Insert Table 2 here---

Robustness Tests

Alternative Ideal Sequences

Our estimation of sequence quality relied on calculating distance from top 10% performing BDVs for radical and incremental innovations, and the extent of the sequence convergence in these top performing BDVs plays a key role in the validity of our quality measures. Although our z-tests indicate that the top performing BDVs follow sequences that are distinguished from the rest of the BDVs, we further investigate to see if there are different archetypes of sequences within the top performing BDVs. Following Sabherwal and Robey (1993), we conducted a cluster analysis based on the inter-sequence distance of top 10% performing BDVs, using

[33]While our main analysis focuses on a processual view of narrators in social media, Appendix C presents the results of analysis when only frequencies of narrators in each platform is considered. These results provide evidence that higher frequencies posts made by personal alias help BDVs with radical innovations whereas higher frequencies of venture alias help BDVs with incremental innovations more.

Ward's (1963) technique. The resulting cluster analysis for incremental and radical innovations in Twitter and AngelList indicatesthe presence of a dominating cluster with higher performance mean compared to other emerging clusters[34]. When only top 8% BDVs are considered, only one cluster emerges, indicating a high-converging selection of BDVs. To further examine the robustness of our findings, we calculated the quality of sequence for the middle 84% of BDVs (we dropped the top and bottom 8% BDVs based on their raised capital) when the quality is estimated similar to our main measure, but only average distance from the top 8% BDVs is considered. Models 9 and 10 in Table 2 present these results. The findings remain qualitatively unchanged to this variation.

Endogneity

It can be argued that a BDV that is more successful in raising capital will attract more positive discussions among its audience and hence experience a more positive WoM. This can suggest that the raised capital affects the positivity of sentiments in both Twitter and AngelList. The reverse causality between the capital raised and the positivity of sentiment of WoM in Twitter and AngelList can be a potential cause for endogeneity in our specification (Greene 2003). Given the panel structure of our data, we utilize the Arellano-Bover/Blundell-Bond system of generalized method of moments (GMM) estimator (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). Therefore, following prior literature, we treat the positivity of sentiment of WoM in the two platforms and their interactions as endogenous covariates (Aral et al. 2012; Bardhan et al. 2013). Then, we conduct a two-step system GMM

[34]The largest cluster accounted for: 88% of top performing BDVs with radical innovations in Twitter, 86% of top performing BDVs with radical innovations in AngelList, 86% of top performing BDVs with incremental innovations in Twitter, and 83% of top performing BDVs with incremental innovations in AngelList. In all four sub-groups, two other clusters were emerged in addition to the dominating high-performing cluster.

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.

This method utilizes the second and longer lagged first differences of the endogenous variables as instruments. The results of AR(2) tests indicate there is no serial correlation in the second-differences of residuals. Further, the Hansen's test of over-identification fails to reject the null hypothesis that the instruments are orthogonal to the error terms, 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. The results in Table 2 (models 11 and 12) show that findings remain qualitatively unchanged after accounting for the threat of endogneiety.

Volume of WoM

In order to further evaluate the robustness of the findings, we run the estimation models while considering the volume of WoM instead of its sentiment positivity. The results are presented in Tables 3 and 4. The findings remain similar, although in the model with the raised capital as the dependent variable the coefficient of sequence quality in either platform becomes insignificant in the presence of the volume of WoM measures. This can further imply a full mediation in the model with the volume of WoM.

---Insert Tables 3 and 4 here---

In order to gain further insights about the cross-effects of non-verbal actions in macro-investor and micro-investor platforms, we conduct our analyses in three sub-samples. In the context of BDVs, we define the technological scope as the main big data area that the BDV's product/service is focused on. Big data technologies cover diverse technological areas, most distinctively, big data security (McAfee and Brynjolfsson 2012), analytics applications (LaValle et al. 2013), and big data infrastructure (e.g., computing) (Jacobs 2009, McAfee and

Brynjolfsson 2012). A review of the existing literature on big data suggests that big data technologies are also diverse in their architectural scope. While some big data technologies (e.g., cloud-based computing structures (Grossman and Siegel 2014)) are at the infrastructural level of the IT architecture (see Weill and Vitale 2002 for a discussion of IT enterprise architecture) some technologies target the analytics application layer (e.g., data modeling applications (Grossman and Siegel 2014)). In addition to these more pronounced technological scopes, a third category exists for big data innovations that are concerned with the security applications that protect large operations of the big data innovations belonging to the two other technological scopes.

We discuss that these three scopes can be different with regards to the type of uncertainty they create for investors; therefore, certain platforms may become more important to deliver non-verbal cues of legitimacy. Tables 5 through 10 present the results for our sub-sample analysis.

---Insert Tables 5 through 10 here---

Although our results for the analytics and infrastructure sub-sample are qualitatively similar to the full sample analysis, the findings of these sub-sample analyses suggest that for the security sub-sample, only the quality of narrator sequence in the micro-investor platform plays a role in increasing the positive sentiment of WoM in both Twitter and AngelList. Moreover, the results suggest that only WoM in the micor-investor platform is positively and significantly associated with the raised capital, although the results of the interaction models indicate that quality of narrator sequence in macro-investor platform adds to the value of the quality of sequence in the micro-investor platform, in both affecting the WoM positivity and raised capital for BDVs pursuing a radical innovation. Further, increasing the positivity of WoM in macro-investor platform increases the effect that the positivity of the micro-investor platform has on the raised capital. Taken together, the results suggest that considered alone, non-verbal cues for investors in the security innovations focus on micro-investor platforms, although in case of radical innovations, the evidence suggest that non-verbal cues from the macro-investment platform can aid the cues of legitimacy from the micro-investor platform. The reason for such findings can be explained by the nature of security innovations and their relevance to public reactions. Existing studies in the context of security breaches suggest that firms endure negative market reactions in the case of such breaches (Gordon et al. 2011; Yayla and Hu 2011) while the adoption of security solutions can be greeted by public support (e.g., Chai et al. 2011). Micro-investor platforms draw on a broader audience, often similar to the future public audience of a firm; therefore, investors might decide to focus their attention on cues received from the communications with this broad audience.

Discussion

Social media plays an important role in helping new ventures access the potential investors and deliver cues that signal legitimacy. Focusing on the non-verbal symbolic actions in a new venture's communication with its audience, this essay draws on the literature on signaling theory and organizational innovation to theorize about the legitimacy signals sent when different narrators are selected to promote the venture. Moreover, and considering the prevalence of multi-platform fundraising, we focus on the cross-effects of non-verbal symbolic actions in one micro-investor (Twitter) and one macro-investor (AngelList) platform. Conceptualizing the non-verbal symbolic actions as a sequence of narrators delivering promoting messages to the audience in the context of BDVs, the findings reveal that ventures that are more successful in raising financial capital follow a similar sequence of narrators when communicating with their audience, depending on the innovation strategy and platform in which the communication is carried out.

Specifically, we found that successful BDVs *alternate* between the messages send by agents internal to the venture (e.g., personal or venture aliases) and those sent by external agents (such as news agencies or individual followers). Therefore, successful BDVs sequentially change the mode of promotion from self- to others'-promotion, or vice versa.

Moreover, our findings suggest that compared to organizational and formal aliases, personal aliases are more emphasized in the critical phases of raising capital (i.e., the beginning and the ending of the fundraising period) when a BDV pursues radical innovations. The results suggest that more personal communications are more effective to reduce the salient threats of newness that radical innovations face. Personal communications reflect on the passion of the individual sending a message. It suggests that the individual sees enough value in promoting the venture to spend his/her own time crafting a message and personally deliver it. On the contrary, with incremental innovations facing a larger threat of smallness, maintaining structural and procedural legitimacy through the utilization of a formal alias becomes more effective. Our findings support our theory that when new ventures follow the norms of communication by delivering messages in social media through an official account instead of a personal one, potential investors become more inclined to invest since following the norms may suggest that the new venture has the required resources and managerial maturity to compete with established firms. Utilizing a formal alias may indicate the presence of social-media management functions in the venture, and that may signal the presence of other important functions in the venture. Moreover, utilizing formal aliases when communicating reflects on the managerial understanding of what are the established norms of communication, thereby, suggesting managerial legitimacy of the venture's founders and employees. Figures 4a and 4b summarize the ideal sequence of narrators in Twitter and AL.

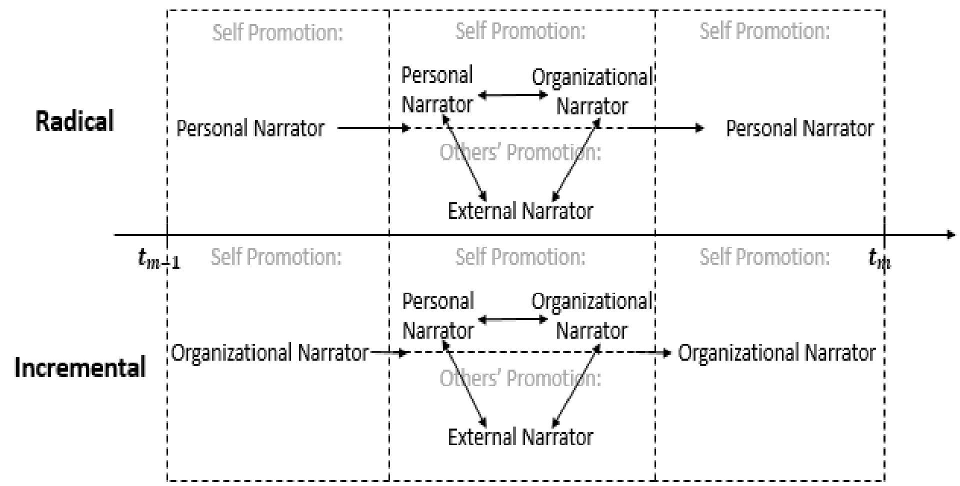


Figure 4a. Ideal Sequence of Narrators in Twitter

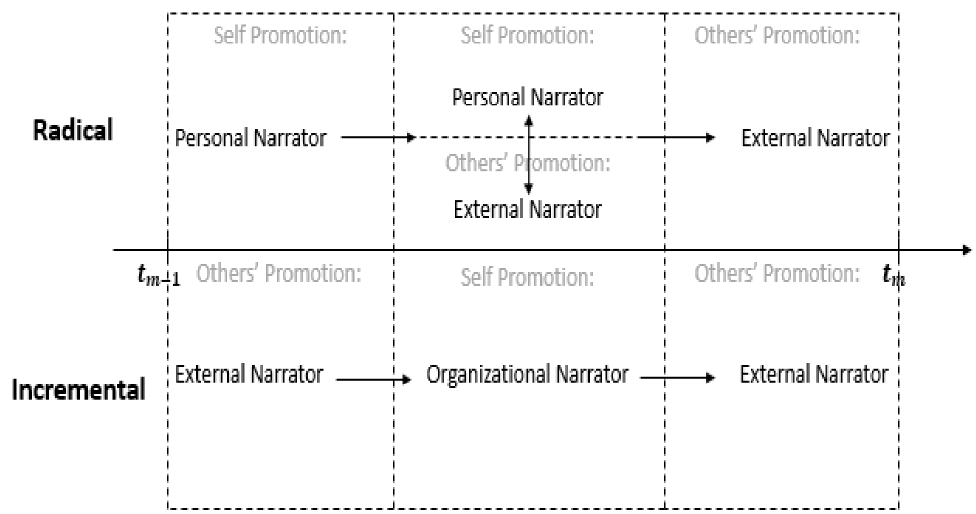


Figure 4b. Ideal Sequence of Narrators in AL

Moreover, the findings of the study suggest that following sequences of narrators similar to those followed by top-performing BDVs increases the positive WoM, as well as the raised capital. More importantly, our findings reveal that the quality of the sequence of narrators in one platform can have effects in the positivity of WoM in the other. These results suggest that macro- and micro-investors may follow legitimacy signals in a platform other than the one in which they have an active presence. Specifically, when investing in radical innovations is considered, the highest level of capital-raising is reached when the qualities of sequence of narrators in both platforms are high. This suggests that the signals in both platforms are conjointly evaluated by investors when radical innovations are considered.

Finally, our sub-sample analysis in the different scopes of the Big Data industry reveals that in the scopes where the innovation is of high sensitivity to the public (i.e., Big Data Security) legitimacy signals are mainly received from a micro-investor platform, with its higher presentation of public opinion. Unlike the case of infrastructural and analytics innovations, the eventual success of a venture active in the scope of security may be more dependent on the public audience as the key stakeholder. Taken together, the results of sub-sample analysis suggest that sub-sections of an industry can be heterogeneous with regards to the type of uncertainty that investors face, and non-verbal symbolic communications pursued by new ventures should match such nuances.

Contributions

The theoretical implications of this study are threefold. First, this study extends the existing literature about symbolic communication in social media platforms (Fischer and Reuber 2014) by showing that in addition to verbal cues, non-verbal signals can also help a new venture promote its innovation. Specifically, drawing on the literature about organizational legitimacy and signaling theory, we provide empirical evidence that selecting narrator of messages sent to the audience operates as a non-verbal cue embedded in organizational communications the social media. These findings also contribute to the existing literature about non-verbal symbolic actions which has evidenced presence of non-verbal cues in mostly physical behaviors but has overlooked non-verbal cues in communication.

Second, the findings of the study extend the existing literature on social media and WoM in two distinct ways. While this literature has mostly focused on the effect of WoM on performance outcomes such as sales (e.g., Dewan and Ramaprasad 2012; Dellarocas et al. 2007; Forman et al. 2008), less attention is paid to organizational actions to manage WoM. Focusing on the context of new ventures, this study suggest that promotional messages sent by an organization to its audience influence WoM in the social media platforms. More importantly, in spite of the prevalence of multi-platforming, no research to date has investigated the cross-effect that WoM in one platform has in another. Our study provides evidence that the audience of a specific platform may follow the cues generated in other platforms, and that WoM in one platform can affect the WoM in the other. Therefore, we provide evidence suggesting that benefits from managerial tactics followed in one platform can spillover to another.

Third, this study contributes to the existing literature on organizational legitimacy by theorizing about the contingent role that innovation strategies play. The existing literature on organizational legitimacy (e.g. Suchman 1995) rarely differentiates legitimacy tactics and their suitability for different firms. However, the literature on strategic management suggests that the best course of action for one firm might not be as effective for another (Venkatraman 1989). Especially for new ventures, with innovation as the core driver of the value, we discuss how different legitimacy tactics suit the type of innovation (radical vs. incremental) a firm pursues.

In addition to its theoretical contributions, this study has two methodological contributions. First, this study provides an alternative method to evaluate the radicalness of innovation in an entrepreneurial firm. The existing literature has mostly utilized self-reported measures (e.g., Ettlie et al. 1984), however, these measures may be limited by common-method biases and social desirability threats (e.g., Podsakoff et al. 2003). We suggest that the text-analysis of reports related to an innovation can provide a more objective alternative measure to evaluate its radicalness. Second, this study presents sequence analysis as a technique to capture symbolic actions that are carried out over time. Although the existing studies describe symbolic actions as those that do not happen at a single point of time (e.g., Fischer and Reuber 2014), these actions are rarely examined over time in an empirical study. Our utilization of sequence analysis enables researchers to evaluate other types of symbolic actions. Further, our approach in utilizing the inter-sequence distance to evaluate the quality of the symbolic actions can be extended to similar contexts.

Managerial Implications

This study provides entrepreneurs a set of actions to be pursed when communicating to potential investors in the social media. First and foremost, our results suggest paying attention to selecting the narrator of a message and alternating between self-promotion and others'-promotion is an effect way to increase positive response from social media followers and eventually increase the raised financial capital. Second, our findings suggest that depending on the type of innovation pursued, entrepreneur should change the mode of self-promotion. Specifically, when radical innovations are pursued, communication in beginning and ending of the capital-raising period should be made through direct personal messages. To the contrary, a formal organizational alias may be utilized in key phases of communication (e.g., beginning and ending of a fundraising campaign) when the venture is focusing on development of an incremental innovation. Third, entrepreneurs should divide their attention between different social media platforms appropriately as investors may look for legitimacy cues in platforms that they are not primarily active in. Especially for those venture pursuing a radical innovation, a simultaneous pursuit of effective legitimacy tactics is met with higher payoffs. Finally, our findings suggest that entrepreneurs in the sections of industry with a more public sensitivity should direct their focus on micro-investing platforms since likely investors pay more attention to reactions in a platform which is more representative of the key stakeholders' opinion.

Limitations

In spite of its contributions, the findings of the study should be interpreted while considering its limitations. First, in our examination of multiple social media platforms, our data is limited to two platforms, Twitter and AngelList. We contend that further examination of cross-platform effect of non-verbal symbolic communication in different platforms can increase the generalizability of these findings. Further, it is possible that BDVs prioritize their use of micro- and macro-platforms differently (e.g., using Twitter as the main channel of communication and AL as a secondary one). Our data is limited to allow us control for this aspect and accounting for such heterogeneity across BDVs' use of their social media platform might change the findings. Moreover, our data is limited in its evaluation of non-verbal symbolic actions carried out outside of social media. Specifically, the existing research suggests that offline face-to-face meetings, especially with macro-investors, are key to promote new ventures (e.g., Birley 1986; Wetzel 1987; Harrison and Mason 1992; Webb et al. 2013; Thai and Turkina 2014). Therefore, additional research considering offline symbolic actions can shed more light on interactions of online and offline symbolic behavior and extend the current findings. Finally, our selection of Big Data industry as the context of the study may limit the generalization of findings. Big Data is considered to be an advanced area in IT (e.g., Chen et al. 2012) and communicational norms of IT entrepreneurial firms may be different from those in the other industries. An examination of similar non-verbal symbolic communications in other industries can shed more light on the robustness of our findings and its applicability to the non-IT industry.

References

Abbott, A. 1995, "Sequence Analysis: New Methods for Old Ideas," *Annual Review of Sociology*pp. 93-113.

Aldrich, H. E., and C. M. Fiol. 1994, "Fools Rush in? the Institutional Context of Industry Creation," *Academy of Management Review* (19:4), pp. 645-670.

Aral, S., E. Brynjolfsson, and M. Van Alstyne. 2012, "Information, Technology, and Information Worker Productivity," *Information Systems Research* (23:3-part-2), pp. 849-867.

Arellano, M., and S. Bond. 1991, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *The Review of Economic Studies* (58:2), pp. 277-297.

Arellano, M., and O. Bover. 1995, "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics* (68:1), pp. 29-51.

Arndt, M., and B. Bigelow. 2000, "Presenting Structural Innovation in an Institutional Environment: Hospitals' use of Impression Management," *Administrative Science Quarterly* (45:3), pp. 494-522.

Avery, D. R., and P. F. McKay. 2006, "Target Practice: An Organizational Impression Management Approach to Attracting Minority and Female Job Applicants," *Personnel Psychology* (59:1), pp. 157-187.

Bardhan, I., V. Krishnan, and S. Lin. 2013, "Research Note-Business Value of Information Technology: Testing the Interaction Effect of IT and R&D on Tobin's Q," *Information Systems Research* (24:4), pp. 1147-1161.

Baron, J. N., and M. T. Hannan. 2002, "Organizational Blueprints for Success in High-Tech Start-Ups: Lessons from the Stanford Project on Emerging Companies," *California Management Review* (44:3), pp. 8-36.

Belleflamme, P., T. Lambert, and A. Schwienbacher. 2014, "Crowdfunding: Tapping the Right Crowd," *Journal of Business Venturing* (29:5), pp. 585-609.

Bertoni, F., M. G. Colombo, and L. Grilli. 2011, "Venture Capital Financing and the Growth of High-Tech Start-Ups: Disentangling Treatment from Selection Effects," *Research Policy* (40:7), pp. 1028-1043.

Birley, S. 1986, "The Role of Networks in the Entrepreneurial Process," *Journal of Business Venturing* (1:1), pp. 107-117.

Blundell, R., and S. Bond. 1998, "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* (87:1), pp. 115-143.

Bolino, M. C., and W. H. Turnley. 1999, "Measuring Impression Management in Organizations: A Scale Development Based on the Jones and Pittman Taxonomy," *Organizational Research Methods* (2:2), pp. 187-206.

Boulding, W., and A. Kirmani. 1993, "A Consumer-Side Experimental Examination of Signaling Theory: Do Consumers Perceive Warranties as Signals of Quality?" *Journal of Consumer Research*pp. 111-123.

Bozeman, D. P., and K. M. Kacmar. 1997, "A Cybernetic Model of Impression Management Processes in Organizations," *Organizational Behavior and Human Decision Processes* (69:1), pp. 9-30.

Burtch, G., A. Ghose, and S. Wattal. 2013, "An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets," *Information Systems Research* (24:3), pp. 499-519.

Caillouet, R. H., and M. W. Allen. 1996, "Impression Management Strategies Employees use when Discussing their Organization's Public Image," *Journal of Public Relations Research* (8:4), pp. 211-227.

Chai, S., M. Kim, and H. R. Rao. 2011, "Firms' Information Security Investment Decisions: Stock Market Evidence of Investors' Behavior," *Decision Support Systems* (50:4), pp. 651-661.

Chen, H., R. H. L. Chiang, and V. C. Storey. 2012, "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly* (36:4), pp. 1165-1188.

Chen, X., X. Yao, and S. Kotha. 2009, "Entrepreneur Passion and Preparedness in Business Plan Presentations: A Persuasion Analysis of Venture Capitalists' Funding Decisions," *Academy of Management Journal* (52:1), pp. 199-214.

Chevalier, J. A., and D. Mayzlin. 2006, "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research* (43:3), pp. 345-354.

Clarke, J. 2011, "Revitalizing Entrepreneurship: How Visual Symbols are used in Entrepreneurial Performances," *Journal of Management Studies* (48:6), pp. 1365-1391.

Colombo, M. G., and L. Grilli. 2010, "On Growth Drivers of High-Tech Start-Ups: Exploring the Role of Founders' Human Capital and Venture Capital," *Journal of Business Venturing* (25:6), pp. 610-626.

Connelly, B. L., S. T. Certo, R. D. Ireland, and C. R. Reutzel. 2011, "Signaling Theory: A Review and Assessment," *Journal of Management* (37:1), pp. 39-67.

Cumming, D. 2007, "Government Policy Towards Entrepreneurial Finance: Innovation Investment Funds," *Journal of Business Venturing* (22:2), pp. 193-235.

Davidson, W. N., P. Jiraporn, Y. S. Kim, and C. Nemec. 2004, "Earnings Management Following Duality-Creating Successions: Ethnostatistics, Impression Management, and Agency Theory," *Academy of Management Journal* (47:2), pp. 267-275.

Dellarocas, C., X. M. Zhang, and N. F. Awad. 2007, "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures," *Journal of Interactive Marketing* (21:4), pp. 23-45.

Dewan, S., and J. Ramaprasad. 2012, "Research Note-Music Blogging, Online Sampling, and the Long Tail," *Information Systems Research* (23:3-part-2), pp. 1056-1067.

Dhar, V. 2013, "Data Science and Prediction," *Communications of the ACM* (56:12), pp. 64-73.

Elitzur, R., and A. Gavious. 2003, "Contracting, Signaling, and Moral Hazard: A Model of Entrepreneurs,'angels,'and Venture Capitalists," *Journal of Business Venturing* (18:6), pp. 709-725.

Ellis, A. P., B. J. West, A. M. Ryan, and R. P. DeShon. 2002, "The use of Impression Management Tactics in Structured Interviews: A Function of Question Type?" *Journal of Applied Psychology* (87:6), pp. 1200.

Elsbach, K. D. 1994, "Managing Organizational Legitimacy in the California Cattle Industry: The Construction and Effectiveness of Verbal Accounts," *Administrative Science Quarterly*pp. 57-88.

Elsbach, K. D., and R. I. Sutton. 1992, "Acquiring Organizational Legitimacy through Illegitimate Actions: A Marriage of Institutional and Impression Management Theories," *Academy of Management Journal* (35:4), pp. 699-738.

Elsbach, K. D., R. I. Sutton, and K. E. Principe. 1998, "Averting Expected Challenges through Anticipatory Impression Management: A Study of Hospital Billing," *Organization Science* (9:1), pp. 68-86.

Ettlie, J. E., W. P. Bridges, and R. D. O'keefe. 1984, "Organization Strategy and Structural Differences for Radical Versus Incremental Innovation," *Management Science* (30:6), pp. 682-695.

Fischer, E., and A. R. Reuber. 2014, "Online Entrepreneurial Communication: Mitigating Uncertainty and Increasing Differentiation Via Twitter," *Journal of Business Venturing* (29:4), pp. 565-583.

Forman, C., A. Ghose, and B. Wiesenfeld. 2008, "Examining the Relationship between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets," *Information Systems Research* (19:3), pp. 291-313.

Gerber, E. M., and J. Hui. 2013, "Crowdfunding: Motivations and Deterrents for Participation," *ACM Transactions on Computer-Human Interaction (TOCHI)* (20:6), pp. 34.

Goffman, E. 2002, "The Presentation of Self in Everyday Life. 1959," *Garden City, NY*.

Golant, B. D., and J. A. Sillince. 2007, "The Constitution of Organizational Legitimacy: A Narrative Perspective," *Organization Studies* (28:8), pp. 1149-1167.

Gordon, L. A., M. P. Loeb, and L. Zhou. 2011, "The Impact of Information Security Breaches: Has there been a Downward Shift in Costs?" *Journal of Computer Security* (19:1), pp. 33-56.

Greene, W. H. 2003. *Econometric Analysis, 5/e*, Pearson Education India.

Grossman, R. L., and K. P. Siegel. 2014, "Organizational Models for Big Data and Analytics," *Journal of Organization Design* (3:1), pp. 20-25.

Harrison, R. T., and C. M. Mason. 1992, "International Perspectives on the Supply of Informal Venture Capital," *Journal of Business Venturing* (7:6), pp. 459-475.

Kim, K., and Hann,I. 2013. "Does Crowdfunding Democratize Access to Capital? A Geographical Analysis," .

LaValle, S., E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz. 2013, "Big Data, Analytics and the Path from Insights to Value," *MIT Sloan Management Review* (21:.

Liu, Y. 2006, "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing* (70:3), pp. 74-89.

Lounsbury, M., and M. A. Glynn. 2001, "Cultural Entrepreneurship: Stories, Legitimacy, and the Acquisition of Resources," *Strategic Management Journal* (22:6-7), pp. 545-564.

Lu, C., Xie,S., Kong,X., and Yu,P. S. 2014. "Inferring the Impacts of Social Media on Crowdfunding," pp. 573-582.

———. 2014. "Inferring the Impacts of Social Media on Crowdfunding," pp. 573-582.

Macht, S. A., and J. Weatherston. 2014, "The Benefits of Online Crowdfunding for Fund-Seeking Business Ventures," *Strategic Change* (23:1-2), pp. 1-14.

MacMillan, I. C., D. M. Kulow, and R. Khoylian. 1989, "Venture Capitalists' Involvement in their Investments: Extent and Performance," *Journal of Business Venturing* (4:1), pp. 27-47.

Martens, M. L., J. E. Jennings, and P. D. Jennings. 2007, "Do the Stories they Tell Get them the Money they Need? the Role of Entrepreneurial Narratives in Resource Acquisition," *Academy of Management Journal* (50:5), pp. 1107-1132.

McAfee, A., and E. Brynjolfsson. 2012, "Big Data: The Management Revolution," *Harvard Business Review* (90:10), Oct, pp. 60-6, 68, 128.

Mollick, E. 2014, "The Dynamics of Crowdfunding: An Exploratory Study," *Journal of Business Venturing* (29:1), pp. 1-16.

Mudambi, S. M., and D. Schuff. 2010, "What Makes a Helpful Review? A Study of Customer Reviews on Amazon. Com," *MIS Quarterly* (34:1), pp. 185-200.

Nagy, B. G., J. M. Pollack, M. W. Rutherford, and F. T. Lohrke. 2012, "The Influence of Entrepreneurs' Credentials and Impression Management Behaviors on Perceptions of New Venture Legitimacy," *Entrepreneurship Theory and Practice* (36:5), pp. 941-965.

Parhankangas, A., and M. Ehrlich. 2014, "How Entrepreneurs Seduce Business Angels: An Impression Management Approach," *Journal of Business Venturing* (29:4), pp. 543-564.

Podsakoff, P. M., S. B. MacKenzie, J. Lee, and N. P. Podsakoff. 2003, "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* (88:5), pp. 879.

———. 2003, "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* (88:5), pp. 879.

Pollock, T. G., and V. P. Rindova. 2003, "Media Legitimation Effects in the Market for Initial Public Offerings," *Academy of Management Journal* (46:5), pp. 631-642.

Rao, H. 1994, "The Social Construction of Reputation: Certification Contests, Legitimation, and the Survival of Organizations in the American Automobile Industry: 1895–1912," *Strategic Management Journal* (15:S1), pp. 29-44.

Rosenbusch, N., J. Brinckmann, and A. Bausch. 2011, "Is Innovation always Beneficial? A Meta-Analysis of the Relationship between Innovation and Performance in SMEs," *Journal of Business Venturing* (26:4), pp. 441-457.

Sabherwal, R., and D. Robey. 1993, "An Empirical Taxonomy of Implementation Processes Based on Sequences of Events in Information System Development," *Organization Science* (4:4), pp. 548-576.

Spence, M. 2002, "Signaling in Retrospect and the Informational Structure of Markets," *American Economic Review*pp. 434-459.

Suchman, M. C. 1995, "Managing Legitimacy: Strategic and Institutional Approaches," *Academy of Management Review* (20:3), pp. 571-610.

Thai, M. T. T., and E. Turkina. 2014, "Macro-Level Determinants of Formal Entrepreneurship Versus Informal Entrepreneurship," *Journal of Business Venturing* (29:4), pp. 490-510.

Thies, F., and M. Wessel. 2014, "The Circular Effects of Popularity Information and Electronic Word-of-Mouth on Consumer Decision-Making: Evidence from a Crowdfunding Platform," .

Timmons, J. A., and W. D. Bygrave. 1986, "Venture Capital's Role in Financing Innovation for Economic Growth," *Journal of Business Venturing* (1:2), pp. 161-176.

Trusov, M., R. E. Bucklin, and K. Pauwels. 2009, "Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing* (73:5), pp. 90-102.

Venkatraman, N. 1989, "The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence," *Academy of Management Review* (14:3), pp. 423-444.

Ward Jr, J. H. 1963, "Hierarchical Grouping to Optimize an Objective Function," *Journal of the American Statistical Association* (58:301), pp. 236-244.

Webb, J. W., G. D. Bruton, L. Tihanyi, and R. D. Ireland. 2013, "Research on Entrepreneurship in the Informal Economy: Framing a Research Agenda," *Journal of Business Venturing* (28:5), pp. 598-614.

Weill, P., and M. Vitale. 2002, "What IT Infrastructure Capabilities are Needed to Implement e-Business Models," *MIS Quarterly Executive* (1:1), pp. 17-34.

Wetzel, W. E. 1987, "The Informal Venture Capital Market: Aspects of Scale and Market Efficiency," *Journal of Business Venturing* (2:4), pp. 299-313.

Yayla, A. A., and Q. Hu. 2011, "The Impact of Information Security Events on the Stock Value of Firms: The Effect of Contingency Factors," *Journal of Information Technology* (26:1), pp. 60-77.

Zhang, Y., and M. F. Wiersema. 2009, "Stock Market Reaction to CEO Certification: The Signaling Role of CEO Background," *Strategic Management Journal* (30:7), pp. 693-710.

Zott, C., and R. Amit. 2007, "Business Model Design and the Performance of Entrepreneurial Firms," *Organization Science* (18:2), pp. 181-199.

Tables of Chapter 4

Table 1. Results with WoM as the Dependent Variable

	WoM measured by sentiment							
	Direct effect				Interaction effect			
	Novel		Incremental		Novel		Incremental	
	Model 1		Model 2		Model 3		Model 4	
DV=	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM
Sequence Quality in Twitter	0.121***	0.094**	0.099**	0.071*	0.138***	0.082**	0.111***	0.065*
Sequence Quality in AL	0.062*	0.069*	0.053**	0.078**	0.052*	0.116***	0.031*	0.091**
Twitter WoM		0.073**		0.066*		0.062*		0.044*
AL WoM	0.058*		0.046*		0.043*		0.021	
Sequence Quality in Twitter * Sequence Quality in AL					0.093**	0.158***	0.018	0.009
N	*2844*	*2844*	*1269*	*1269*	*2844*	*2844*	*1269*	*1269*
Wald's Chi	*5272.33*	*6317.14*	*4398.12*	*5622.67*	*6718.45*	*7233.24*	*5324.89*	*4315.89*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 2. Results with Raised Capital as the Dependent Variable

	WoM measured by sentiment							
	GLS				Alternative Sequence		AB-GMM	
	Direct effect		Interaction effect		Interaction effect		Interaction effect	
	Novel	Incremental	Novel	Incremental	Novel	Incremental	Novel	Incremental
	Model 5	Model 6	Model 7	Model 8	Model 9	Model10	Model 11	Model 12
DV=	Raised capital		Raised capital		Raised Capital		Raised capital	
Sequence Quality in Twitter	0.043*	0.033*	0.038*	0.042*	0.031*	0.065**	0.026*	0.007
Sequence Quality in AL	0.051*	0.028*	0.017*	0.017*	0.011#	0.014*	0.009	0.002
Twitter WoM	0.205***	0.211*	0.229***	0.114***	0.113***	0.182***	0.098***	0.089**
AL WoM	0.082**	0.074*	0.073*	0.044*	0.058*	0.044#	0.033#	0.018#
Sequence Quality in Twitter * Sequence Quality in AL			0.092*	0.031	0.203***	0.014	0.073*	0.003
Twitter WoM * AL WoM			0.127***	0.011	0.123***	0.008	0.118***	0.005
N	*2844*	*1269*	*2844*	*1269*	*2986*	*1332*	*2844*	*1269*
Wald's Chi	*6333.12*	*7809.32*	*8178.34*	*7645.23*	*5321.3*	*3208.5*	*8311.1*	*8340.47*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
For GLS estimations, corrections for panel specific AR1 and Heteroskedasticity are used.

Table 3. Results with WoM as the Dependent Variable (Volume of WoM is Considered)

	WoM measured by volume							
	Direct effect				Interaction effect			
	Novel		Incremental		Novel		Incremental	
	Model 13		Model 14		Model 15		Model 16	
DV=	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM
Sequence Quality in Twitter	0.211***	0.115***	0.257***	0.083**	0.087**	0.119**	0.167***	0.089*
Sequence Quality in AL	0.028*	0.072**	0.021#	0.092***	0.041*	0.195***	0.028#	0.073*
Twitter WoM		0.091***		0.050*		0.032*		0.033*
AL WoM	0.062**		0.039**		0.038*		0.015#	
Sequence Quality in Twitter * Sequence Quality in AL					0.115***	0.272***	0.003	0.011
N	*2844*	*2844*	*1269*	*1269*	*2844*	*2844*	*1269*	*1269*
Wald's Chi	*6718.23*	*7129.25*	*5564.33*	*6701.23*	*7782.48*	*8095.34*	*6624.24*	*7639.17*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;

*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*

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

Table 4. Results with Raised Capital as the Dependent Variable (Volume of WoM is Considered)

	WoM measured by volume					
	GLS				AB-GMM	
	Direct effect		Interaction effect		Interaction effect	
	Novel	Incremental	Novel	Incremental	Novel	Incremental
	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
DV=	Raised capital		Raised capital		Raised capital	
Sequence Quality in Twitter	0.022#	0.003	0.028#	0.010#	0.002	0.023*
Sequence Quality in AL	0.019	0.005	0.015	0.012	0.003	0.014*
Twitter WoM	0.355***	0.407***	0.375***	0.227***	0.082*	0.171***
AL WoM	0.071*	0.098**	0.062*	0.039*	0.025#	0.028*
Sequence Quality in Twitter * Sequence Quality in AL			0.110**	0.025	0.062#	0.005
Twitter WoM * AL WoM			0.176***	0.009	0.221*	-0.008
N	*2844*	*1269*	*2844*	*1269*	*2844*	*1269*
Wald's Chi	*5582.56*	*6689.47*	*7612.28*	*8124.72*	*3298.1*	*2678.33*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
For GLS estimations, corrections for panel specific AR1 and Heteroskedasticity are used.

Table 5. Results with WoM as the Dependent Variable- Security Sub-Sample

	WoM measured by sentiment							
	Direct effect				Interaction effect			
	Novel		Incremental		Novel		Incremental	
	Model 23		Model 24		Model 25		Model 26	
DV=	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM
Sequence Quality in Twitter	0.144***	0.142***	0.084*	0.062*	0.229***	0.128***	0.173***	0.127***
Sequence Quality in AL	0.022	0.012	0.013	0.004	0.003	0.008	0.015	0.021#
Twitter WoM		0.114***		0.115*		0.119***		0.094**
AL WoM	0.006		0.008		0.005		0.006	
Sequence Quality in Twitter * Sequence Quality in AL					0.063*	0.141***	*0.002*	*0.004*
N	*740*	*740*	*342*	*342*	*740*	*740*	*342*	*342*
Wald's Chi	*5372.54*	*6186.87*	*5328.34*	*4876.72*	*5633.25*	*6772.83*	*5843.69*	*6671.32*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
GLS estimation with corrections for panel specific AR1 and Heteroskedasticity is used.

Table 6. Results with Raised Capital as the Dependent Variable- Security Sub-Sample

	WoM measured by sentiment			
	Direct effect		Interaction effect	
	Novel	Incremental	Novel	Incremental
	Model 27	Model 28	Model 29	Model 30
DV=	Raised capital		Raised capital	
Sequence Quality in Twitter	0.005	0.008	0.004	0.003
Sequence Quality in AL	0.004	0.011	0.008	0.008
Twitter WoM	0.326***	0.242***	0.092***	0.072***
AL WoM	0.007	0.002	0.015	0.004
Sequence Quality in Twitter * Sequence Quality in AL			0.083*	0.002
Twitter WoM * AL WoM			0.332***	0.002
N	*740*	*342*	*740*	*342*
Wald's Chi	*7334.69*	*7881.45*	*8234.54*	*8127.29*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
For GLS estimations, corrections for panel specific AR1 and Heteroskedasticity are used.

Table 7. Results with WoM as the Dependent Variable- Analytics Sub-Sample

	WoM measured by sentiment							
	Direct effect				Interaction effect			
	Novel		Incremental		Novel		Incremental	
	Model 31		Model 32		Model 33		Model 34	
DV=	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM
Sequence Quality in Twitter	0.221***	0.031#	0.026*	0.032**	0.118***	0.086**	0.088**	0.084**
Sequence Quality in AL	0.098***	0.152***	0.062*	0.095**	0.082**	0.153***	0.048*	0.141***
Twitter WoM		0.019#		0.023*		0.003		0.011#
AL WoM	0.062**		0.078**		0.066*		0.062**	
Sequence Quality in Twitter * Sequence Quality in AL					0.188***	0.213***	*0.004*	*0.011*
N	*1248*	*1248*	*519*	*519*	*1248*	*1248*	*519*	*519*
Wald's Chi	*4356.98*	*5612.78*	*57812.35*	*6783.58*	*7322.68*	*6379.33*	*7334.69*	*7981.12*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;

*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*

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

Table 8. Results with Raised Capital as the Dependent Variable- Analytics Sub-Sample

	WoM measured by sentiment			
	Direct effect		Interaction effect	
	Novel	Incremental	Novel	Incremental
	Model 35	Model 36	Model 37	Model 38
DV=	Raised capital		Raised capital	
Sequence Quality in Twitter	0.013#	0.035**	0.001	0.004
Sequence Quality in AL	0.018#	0.013#	0.008	0.012
Twitter WoM	0.081*	0.061*	0.082**	0.060**
AL WoM	0.248***	0.189***	0.312***	0.253***
Sequence Quality in Twitter * Sequence Quality in AL			0.041*	0.008
Twitter WoM * AL WoM			0.182***	-0.005
N	*1248*	*519*	*1248*	*519*
Wald's Chi	*7652.21*	*6537.82*	*8128.9*	*8256.18*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
For GLS estimations, corrections for panel specific AR1 and Heteroskedasticity are used.

Table 9. Results with WoM as the Dependent Variable- Infrastructure Sub-Sample

	WoM measured by sentiment							
	Direct effect				Interaction effect			
	Novel		Incremental		Novel		Incremental	
	Model 39		Model 40		Model 41		Model 42	
DV=	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM	Twitter WoM	AL WoM
Sequence Quality in Twitter	0.314***	0.061*	0.012#	0.025**	0.102**	0.01	0.082*	0.006
Sequence Quality in AL	0.082**	0.182***	0.078**	0.098***	0.118***	0.287***	0.022#	0.203***
Twitter WoM		0.018#		0.010#		0.004		0.003
AL WoM	0.071*		0.121***		0.048*		0.032*	
Sequence Quality in Twitter * Sequence Quality in AL					0.097***	0.150***	*0.009*	*0.015*
N	*856*	*856*	*408*	*408*	*856*	*856*	*408*	*408*
Wald's Chi	*6378.22*	*7345.9*	*5478.34*	*5682.22*	*5377.18*	*6439.86*	*7845.63*	*6854.32*

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;

*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*

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

Table 10. Results with Raised Capital as the Dependent Variable- Infrastructure Sub-Sample

	WoM measured by sentiment			
	Direct effect		Interaction effect	
	Novel	Incremental	Novel	Incremental
	Model 43	Model 44	Model 45	Model 46
DV=	Raised capital		Raised capital	
Sequence Quality in Twitter	0.012*	0.026**	0.002	0.003
Sequence Quality in AL	0.018*	0.013#	0.011#	0.009
Twitter WoM	0.052*	0.021#	0.062*	0.040*
AL WoM	0.126**	0.317***	0.224***	0.184**
Sequence Quality in Twitter * Sequence Quality in AL			0.038#	0.007
Twitter WoM * AL WoM			0.192***	0.002
N	856	408	856	408
Wald's Chi	5332.21	6782.63	7319.42	8102.8

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
For GLS estimations, corrections for panel specific AR1 and Heteroskedasticity are used.

Appendix A. Correlation Matrix

		Mean	S.D.	1	2	3	4	5	6
1	Sequence quality in Twitter	0.19	0.25						
2	Sequence quality in AL	0.23	0.31	0.18**					
3	Twitter WoM Sentiment	0.58	0.29	0.23***	0.16*				
4	Twitter WoM Volume	118.21	43.16	0.19***	0.07#	0.12*			
5	AL WoM Sentiment	0.52	0.26	0.14*	0.28***	0.05	0.07		
6	Al WoM Volume	32.42	18.11	0.08#	0.17*	0.02	0.11#	0.10*	
7	Raised Capital	1.08	0.32	0.27***	0.32***	0.48***	0.33**	0.18**	0.13#

*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001; N= 4,113.*

Appendix B. Illustrative Example of Social Media Promotion

Personal Alias (Twitter)	**Barricade IO Retweeted** David Coallier @davidcoallier And this happened (@barricadeio): https://barricade.io/
Venture Alias (Twitter)	**Barricade IO @barricadeio** The foundations of #infosec explained in an infographic https://blog.barricade.io/the-art-of-security/?utm_source=socialsharing&utm_medium=infographic&utm_term=The%20Art%20of%20Security%20Information%20Security%20Infographic&utm_content=infographic&utm_campaign=ArtofSecurityInfographic …#infographic#DevOps#Design
News (Twitter)	**Barricade IO Retweeted** eForensics Magazine @eForensics_Mag The Art of Security - Explained Visually by @barricadeiohttp://bit.ly/2bf9EOs #cybersecurity#cybercrime#dfir
Follower (Twitter)	**Barricade IO Retweeted** Charlie Taylor @ChasTaylor Hot off the presses: Sophos has acquired Cork-based start-up @barricadeio, headed by @davidcoallier
Personal Alias (AngelList)	**David Coallier commented on Barricade** Hey Paul, the round has been opened for a while on Angel List. Would love to jump on a call to clarify when you have time :)
Venture Alias (AngelList)	**Barricade** Hey everyone! We've completely redefined our onboarding and would love if you'd give it a try! https://barricade.io — Cheers!
News (AngelList)	**independent.ie** Cork IT security startup to create 35 jobs - Independent.ie The company has been set up by serial Irish technology entrepreneur David Coallier, who co-founded Dublin-based Orchestra, sold to US multinational firm Engineyard in 2011. Barricade's expansion comes shortly after an initial €1m funding round. Investors

Appendix C. The Effect of Narrator Frequencies on Capital Raised

	Novel	Incremental
	Model C1	Model C1
DV=	Raised capital	
Frequency of Personal Alias (Twitter)	0.112***	$0.019^{\#}$
Frequency of Venture Alias (Twtter)	0.023	0.076**
Frequency of News (Twitter)	0.065**	0.054**
Frequency of Follower (Twitter)	0.083***	0.079**
Frequency of Personal Alias (AL)	0.203***	0.011
Frequency of Venture Alias (AL)	$0.033^{\#}$	0.215***
Frequency of News (AL)	0.037*	0.062**
Twitter WoM	0.029*	$0.014^{\#}$
AL WoM	0.110**	0.081*
N	2844	1269
Wald's Chi	4827.1	6339.3

Coefficients of variables number of employees, education of employees, positive language of promotional text, and dummies representing the scope of the BDV, type of innovation (B2B or B2C), location, and BDV's year of establishment are not reported for brevity;
*#p < 0.10, * p < 0.05, ** p < 0.01, *** p< 0.001;*
For GLS estimations, corrections for panel specific AR1 and Heteroskedasticity are used.

Chapter 5: Conclusions

This dissertation is motivated by contributing to two emerging topics in IS: new IT ventures, and the Big Data industry. On the one hand, although IT entrepreneurial firms have been pioneers of innovation in the field, making the Silicon Valley the symbol of IT advancements, research has been lacking to understand how these small, organic, and sometimes fragile organizations grow into giants that define the industry's norms and trends. Specifically, the field's understanding of the strategic factors influencing the economic "success" of new IT ventures has been limited. On the other hand, the organizational research on Big Data technologies – specifically, how they emerge and grow as IT innovations and how firms benefit from investing them – is still in the infancy stage (Goes 2014). With most Big Data innovations driven by new ventures, this dissertation seizes the opportunity to understand the strategic factors that affect the economic success of new Big Data ventures (i.e., BDVs).

While understanding the strategies followed by new IT ventures is the core theoretical *phenomenon* of interest in this dissertation, this phenomenon is investigated in the rich *context* of Big Data. This is done in a study of three essays. In developing the essays, we have changed our theoretical focus from the phenomenon to the context, and vice versa. Focusing on the Big-Data-specific value propositions offered by BDVs, Chapter 2 has examined the context of Big Data and shed light on the hierarchy of Big Data technologies' 4V emphases. By contrast, essays 2 and 3 have focused on the phenomenon of new IT ventures theoretically, and described this phenomenon in the highly relevant context of Big Data. In understanding the entrepreneurial success, essay 2 has drawn a distinction between the Big Data and a medical context, whereas, essay 3 has pointed to the differences among certain areas within the Big Data context. As a whole, this dissertation contributes to the literature on: new IT ventures, and Big Data. Below, we explain the contributions of each essay in detail.

Chapter 2 (Essay 1)

Essay 1 is primarily focused on understanding how value is created by Big Data technologies. The existing literature on Big Data defines Big Data technologies as those helping organizations handle data that has a high *volume* and fast flow to organizational systems (*volume*), and is gathered from various sources and in various formats (*variety*), with assuring its *veracity* being a challenging task (Chen et al. 2012). These 4V challenges of Big Data, and the Big Data technology's roles in handling these challenges is almost undisputed. However, the existing literature is unclear about the relative value of tackling each V by different Big Data technologies. Specifically, it is interesting to know whether Big Data technologies are homogeneous with regards to their intent in tackling the 4V challenges, or there exists some heterogeneity.

In this essay, we discussed that Big Data technologies include a wide architectural range, from infrastructural applications that allow distributed storage and retrieval of data, to analytical applications that use distributed computing along with advanced statistical algorithms to identify and model complex trends and behaviors. Therefore, the role of emphasizing each V was studied in each architectural scope. Our results suggested that for infrastructural technologies, only emphasizing volume and velocity creates value. However, as the technology moves up the ladder of architectural hierarchy, emphasizing the veracity and variety aspects become more relevant. These results suggest that the 4Vs are not homogeneous with regards to value that tackling them creates. Rather, depending on the scope of the Big Data technology, certain aspects become more important. The findings also suggest that handling volume and velocity of today's data is the essential part of Big Data technologies, regardless of their scope.

In addition to bringing clarity regarding the value of emphasizing each of the 4Vs of Big Data, the findings show that the verbal communication of a new venture's value propositions effectively influences the financial success of the venture itself, as well as the value created for its investors. One finding in this essay suggests that verbally communicating value propositions by a third party (e.g., a news piece, or blog post about the venture) has an effect similar to when the message is delivered by the venture itself. These findings can direct entrepreneurs' attention towards the third party coverage of their venture as a reliable source to communicate value propositions to the investors.

Chapter 3 (Essay 2)

While communicating value propositions are important to convince investors, embeddedness in social networks is another means through which entrepreneurs can promote their product/service, and access valuable resources that are otherwise inaccessible or can only be accessed at a higher price (Witt 2004). The existing literature on success of new ventures has focused on network ties that allow accessing financial capital. Especially at their later stages of development, where new ventures become economically viable and competitive, financial capital is essential to maintain a rapid growth. Nonetheless, the role of network embeddedness in the development of a new venture's innovation in the early stages of development is less understood. The existing literature (e.g., Brüderl and Preisendörfer 1996, Jenssen and Greve 2002, Florin et al. 2003) has focused on new ventures at the later stages of development (e.g., initial public offering, IPO) and therefore, the focus has been the access to the much needed financial capital, but accessing intellectual capital has remained understudied. Therefore, the relevance of the network embeddedness to the intellectual capital necessary for development of innovations is overlooked. Specifically, Big Data provides a rich context to understand the role that networks play in the development of innovations. We discussed that Big Data technologies have the characteristics of a technological area where innovations can be *socially-constructed*. Focusing on the literature on IT innovations (e.g., Couger 1973; Kautz et al. 2007), we identified the educational and professional networks as networks that can supply the intellectual capital needed to develop Big Data innovations.

Our findings suggest that having educational and professional ties to other ventures improve the economic success of a BDV. We find that these results are in sharp contrast to the observations from a comparable industry, i.e., medical devices, where we failed to find any evidence that suggests inter-venture educational or professional ties help a new venture become economically successful. These results involve important implications. Notably, the findings suggest that Big Data technologies are developed socially and through associative educational and professional ties. The existing networks literature suggests that entrepreneurs should spend time to create social ties with individuals and organizations that can provide access to financial capital. Our findings suggest that in addition to these networking activities, entrepreneurs, especially those in industries that resemble the Big Data industry, should consider their embeddedness in networks that can supply access to intellectual capital. New ventures have limited resources to recruit a limited number of employees in their early stages of development. One implication of our findings is that entrepreneurs can use employee recruitment as a means to better embed their venture in the knowledge network of new ventures where technological innovations are co-constructed. Screening a prospective employee's educational and professional background and assessing its relevance, i.e., the degree of similarity or distinctiveness, to the employees of other ventures in the industry can help new ventures become more successful.

Also, another finding in this essay suggests that a separate consideration of networks of different ties can resolve some of the equivocal findings of the previous literature. For example, the previous literature (Elfting and Hulsink 2003) suggests that a mix of network cohesions, i.e., density, and structural holes is required to develop radical innovations. However, network cohesion and structural holes can rarely co-exist in the same network. Nonetheless, if two networks are structurally different, one can supply a venture with the needed cohesion, while the other can supply access to structural holes. Using Kendall's rank correlation between the structural features, e.g., network density or restrictedness, of two different networks we showed how two networks can be compared to assess their structural differences. Moreover, we empirically validated the thesis that structurally-different networks can provide a simultaneous "mix" of seemingly-paradoxical network structures. The previous research encourages superimposing networks of different ties because doing so allows for considering multiplex relationships between the network edges. However, as networks start becoming different, the likelihood of having multiplex ties in the superimposed network subsides, and instead the likelihood of maintaining ambivalence, i.e. access to networks with seemingly paradoxical features, for actors of the network increases. Essay 2, provides an example of where a separate consideration of networks of different ties illuminates the importance of network ambivalence for ventures pursuing a radical innovation.

Chapter 4 (Essay 3)

Essay 1 points to the importance of communicating the worth of a venture to its investors, and essay 2 points to the importance of network embeddedness. Social media provides a unique platform for a new venture to both communicate its worth, and create ties with macro- and micro-investors. Therefore, essay 3 studied the successful promotional strategies that BDVs pursue in their social media. The current literature (Fischer and Rueber 2014) has examined the effect of the verbal content of promotional messages in social media. Similarly, our findings in essay 1 indicate the importance of the verbal communication of the venture's value propositions to the investors. However, promotional strategies can extend beyond verbal communications. Specifically, the previous literature suggests that entrepreneurs often involve in symbolic communications with investors, signaling certain qualities through executing a sequence of actions. This essay strived to understand the means through which symbolic communication is carried in social media. We explained that social media allows promotional messages to be communicated by different narrators, and that following a sequence of narrators can establish a form of symbolic communication by itself. We find that over time, the most successful BDVs *alternate* the narrators of their promotional messages, and avoid a monotonic communication. Moreover, our findings suggest that the beneficial sequence of narrators differ for ventures pursuing radical and incremental innovations. While the previous literature encourages entrepreneurs to manage the content of their messages in social media, our findings suggest that selecting the source of delivering the message is also of important. Moreover, our results point to the superiority of certain rhythms in narrating, suggesting that not only it matters who narrates the message, it also matters when that narrator delivers it. Also, we showed that the beginning and the ending periods of a fundraising campaigns are critical points at which the most influential narrators, depending on the radicalness of strategy, communicate with the investors.

A second contribution of this essay is providing evidence regarding the cross-platform effects. Specifically, we show that ventures in the today's world, broadcasting to micro- and macro-investors in different platforms, should coordinate their promotional efforts. Our findings suggest that strategies pursued in one platform affect the positive reactions by the audience in another platform, especially in the case of the more disruptive and radical innovations. Investors face more uncertainty when considering investment in radical innovations. Our results show that in the presence of such uncertainty, the search for competency signals can extend to the symbolic communications that are originally intended to other audiences.

References

Brüderl, J., and P. Preisendörfer. 1998, "Network Support and the Success of Newly Founded Business," *Small Business Economics* (10:3), pp. 213-225.

Chen, H., R. H. L. Chiang, and V. C. Storey. 2012, "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly* (36:4), pp. 1165-1188.

Couger, J. D. 1973, "Curriculum Recommendations for Undergraduate Programs in Information Systems," *Communications of the ACM* (16:12), pp. 727-749.

Elfring, T., and W. Hulsink. 2003, "Networks in Entrepreneurship: The Case of High-Technology Firms," *Small Business Economics* (21:4), pp. 409-422.

Florin, J., M. Lubatkin, and W. Schulze. 2003, "A Social Capital Model of High-Growth Ventures," *Academy of Management Journal* (46:3), pp. 374-384.

Fischer, E., and A. R. Reuber. 2014, "Online Entrepreneurial Communication: Mitigating Uncertainty and Increasing Differentiation Via Twitter," *Journal of Business Venturing* (29:4), pp. 565-583.

Goes, P. B. 2014, "Editor's Comments: Big Data and IS Research," *MIS Quarterly* (38:3), pp. iii-viii.

Jenssen, J. I., and H. F. Koenig. 2002, "The Effect of Social Networks on Resource Access and Business Start-Ups," *European Planning Studies* (10:8), pp. 1039-1046.

Kautz, K., S. Madsen, and J. Nørbjerg. 2007, "Persistent Problems and Practices in Information Systems Development," *Information Systems Journal* (17:3), pp. 217-239.

Witt, P. 2004, "Entrepreneurs' Networks and the Success of Start-Ups," *Entrepreneurship & Regional Development* (16:5), pp. 391-412.