Digital Startup Access to Venture Capital Financing: What Signals Quality?

ABSTRACT

What signals quality for digital startups seeking access to external finance? Analyzing a unique dataset from India, we investigate the impact of traditional quality signals (e.g., the founders' years of experience, prior industry experience); networking signals (e.g., degrees from elite educational institutes, the breadth of an entrepreneurial team); and digital signals (e.g., the social media presence of the startup on multiple social media sites) on the access to venture capital financing. We find that while networking and digital signals positively impact access to financing, traditional human capital signals do not have any significant impact on the process.

1. INTRODUCTION

Entrepreneurial startups play a fundamental role in the promotion of innovation and economic growth (Acs & Audretsch, 1988; Acs et al., 2008; Audretsch, 2007a and 2007b; Audretsch et al., 2009; Baumol, 1996; Chavis et al., 2011; Cumming & Johan, 2014; Cumming et al., 2014; Fairlie & Chatterji, 2013; Klapper & Love, 2011; Marcotte, 2012; McMullen, 2011; Naude, 2010; Stam & Wennberg, 2009; Thurik et al., 2008). The creation of new entrepreneurial and innovative ventures requires capital financing and, as such, there is a large body of research looking into access to entrepreneurial finance for entrepreneurs and startups (Bhide, 1992; Bonini et al., 2012; Fossen, 2014; Nahata, 2008; Wang & Wang, 2012; Li et al., 2016). We know that sustained financing can ensure high levels of growth and survival of new ventures (Cosh et al., 2009; Smallbone et al., 2003; Storey, 2016; Van Auken & Carter, 1989) while lack of financing can result in low levels of growth and an increased likelihood of failure (Alsos et al., 2006; Basu & Parker, 2001). As financing is crucial for startups not only at the initial stages but also at the later stages for continued growth and survival, extant research has sought to determine the factors that play a significant role in access to finance, such as the human capital of the founders (Almus & Nerlinger, 1999; Colombo & Grilli, 2005; Cressy, 1996; Cumming & Johan, 2008a; Stuart & Abetti, 1990; Westhead & Cowling, 1995) and founders' social networks (Goh et al., 2013; Hochberg et al., 2007; Luo et al., 2013) .

Human capital plays a significant role in entrepreneurial endeavors. Researchers have divided human capital into two broad categories: formal and informal. Formal signifies individual educational qualifications, skills, and abilities, whereas informal signifies human capital developed through work and familial experiences. We know that educational investments and work experience can translate into economic advantages (Becker, 1964; Killeen et al., 1999; Langelett, 2002) and, if applied towards an entrepreneurial activity, can result in improved entrepreneurial judgment (Baron & Ensley, 2006; Corbett, 2005; McGrath & MacMillan, 2000; Parker, 2006; Ronstadt, 1988; Shane, 2000; Wiklund & Shepherd, 2003) and forecasting ability (Clement, 1999; Mikhail et al., 1997). It is clear that the impact of human capital on entrepreneurial activity and judgment has been previously widely studied in more developed economies. There is however limited empirical evidence on the role of human capital in startup financing for firms in developing or emerging markets where institutions are arguably weaker, and informal quality signals are much more important to mitigate information asymmetry. In this paper we analyze Indian tech startups to determine the extent formal and informal human capital signals serve as positive signals to mitigate information asymmetries and potentially impact access to venture capital (VC) for Indian entrepreneurs. Our formal and informal measures include total years of experience, the type of work experience (technical, founder, or consultant), the degree to which an elite educational institute provides access to a network of resources, and the breadth of the entrepreneurial team.

In India, technology has been a major driver of innovation for the last 25 years. Major business opportunities have surfaced in the technological front; consequently, there has been exponential growth in the number of startups, which has attracted investments from a large number of venture capitalists (VCs). From 2012-2017, reports show a significant increase in investments by VCs in Indian startups. The transaction value has increased over 13.5 times (from $94 million in 2011 to $1.275 billion in 2016)[1]. In 2017, investments by VCs in the country reached record levels at $26.5 billion.

With such rapid growth, policymakers face considerable challenges. One challenge is mitigating the inefficiency of the matching process between investors and new technological startups, especially in a financial market which still largely remains imperfect (e.g. Colombo & Grilli, 2005, 2009). In India, graduates from top engineering colleges are no longer restricted to only joining the corporate world; thus, those with engineering, mathematical, and analytical skills are increasingly incentivized to create their own entrepreneurial firms. A report published by NASSCOM[2] states that 50% of the founders of new firms have engineering backgrounds, 25% of them have management backgrounds, and 25% have other educational qualifications. In 2018, nearly half of the startups in India had one or more founders who studied in one or more of the country's top four engineering and management colleges: the IITs[3], IIMs[4], BITS[5], or the Indian School of Business[6]. In the United States, we observe the same trend in relation to Harvard, Stanford, and MIT[7] according to Pitchbook[8] and Crunchbase statistics. These considerations raise our initial question of whether the traditional human capital signal of previous work experience continues to signal quality to investors, as suggested by extant research. Our follow-up question is whether a degree from an elite institute, which may signal quality and increased social capital due to a higher probability of access to a

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[1] PwC report 2016

[2] NASSCOM stands for the National Association of Software and Service Companies, a nonprofit organization established in 1988. It initiated a program called 10000 Startups in 2013. The purpose is to support the impact of 10000 startups in India by 2023.

See the full report at: https://smartnet.niua.org/sites/default/files/resources/nasscom-start-up-report-2017.pdf.

[3] Indian Institute of Technology, a premier engineering college.

[4] Indian Institute of Management, a premier business college.

[5] Birla Institute of Technology, a premier engineering college.

[6] See the full report on at: https://www.kalaari.com/magazine/india-tech-founders-does-alma-mater-matter

[7] Massachusetts Institute of Technology, United States of America.

[8] PitchBook Data, Inc. is a SAAS company founded in March, 2007. It delivers data, research, and technology covering the private capital markets. To collect data, it uses machine learning and natural language processing. The company's core product is the PitchBook Platform, a subscription-only database.

network of high quality and successful alumni and other social connections, results in greater ease of obtaining startup financing from VCs.

We believe another key factor in gaining startup financing is digital network signaling, or using social networks to amass numbers of followers on multiple sites such as Twitter, LinkedIn, and Facebook. Prior research has already linked social capital to the propensity for investors to invest in the Australian crowdfunding context, and we seek to extend this research to our analysis of Indian technology startups (Ahlers et al., 2015). Startups and founders who successfully network and build relationships digitally with their consumers build a successful brand image, which serves as a positive signal to VCs. Previous studies have shown the effectiveness of social media in promoting word-of-mouth information diffusion (Aral et al., 2013; Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Forman et al., 2008; Zhu & Zhang, 2010) in marketing goods and services (Aral et al., 2013; Bharadwaj et al., 2013) and by serving as a platform for greater consumer engagement and participation (Chen et al., 2015; Ghose & Han, 2011; Goes et al., 2014; Li & Wu, 2018; Miller & Tucker, 2013). In this study, we hand collect information from various social media networks (LinkedIn, Twitter, and Facebook) to determine the strength of the startup's digital network and how it impacts a startup's access to financing.

By extending Crane & Hartwell (2019), we link signaling theory with human capital theory and social capital theory to test our developed hypotheses. We collected data from 102 startups that obtained funding between the years 2014-2017. To address potential survivorship bias, we included both failed and active startups. Our results are not only illuminating but also counter-intuitive. We find that the networking and digital signals evidenced by a degree from an elite educational institute (India or abroad), the breadth of the entrepreneurial team (number of founders), and the higher the social media fan following positively impacts access to finance. Founders' years of experience, as well as their prior industry experience as a founder, more specifically their prior experience as technical engineers and consultants, do not show any impact on financing. These findings, related to traditional human capital signals, are rather unexpected as extant research (Baum & Silverman, 2004; Beckman et al., 2007; Burton, 2002; Gompers & Lerner, 2001; Hsu, 2007) using data from developed countries (mainly the US and Europe) show contrasting results. These finding can have several implications for digital entrepreneurs, policymakers, and for VCs, especially in developing countries other than India.

We believe that this study makes important contributions to the existing literature on VC financing (Audretsch et al., 2012; Baum & Silverman 2004; Cao & Hsu, 2011; Conti et al., 2013; Cumming & Johan, 2014; Greenberg, 2013; Häussler et al., 2012; Hoenen et al., 2014; Hsu & Ziedonis, 2013; Mann & Sager, 2007; Cumming & Zhang, 2016), as this study is the first empirical study, to the best of our knowledge, which links human capital theory, social capital theory, and signaling theory to show the impact of human capital and social capital on obtaining VC financing in the developing market context.

The remaining sections of this paper are organized as follows. We begin by reviewing the relevant literature on signaling; the problems of asymmetry, human capital, and social networking; and then we use this research to develop our hypotheses and theoretical framework in Section 2. We describe the research method, data collection, and variables used to test the hypotheses in Section 3. We present our results of multivariate logistic regressions and our robustness tests in Section 4. We conclude and discuss the limitations of our research in Section 5.

2. THEORETICAL BACKGROUND AND HYPOTHESES

Evans & Bahrami (1995) suggest that technological startups[9] are prone to high levels of business risk, changing consumer preferences, fast-changing technology, and a shortened product life cycle. To establish themselves in such a complex and dynamic environment, startups need continued access to external financing as lack of adequate financing has been shown to increase the likelihood of failure (Aspelund et al., 2005; Carter & Van Auken, 2005; Cassar, 2004; Coleman, 2000; Gaskill et al., 1993; Sandberg & Hofer 1987). Inadequate access to financing also affects the growth potential of new ventures. VC literature finds that under-capitalized firms experience lower levels of growth (Alsos et al., 2006; Chandler & Hanks, 1998). A recent research report[10] showed that more than 90% of startups fail. Similarly, in India, a study conducted by IBM found that more than 90% of startups in India fail in the first five years owing to lack of pioneering innovation and funding. New ventures in India may face heightened barriers to traditional sources of financing due to higher institutional burdens, resulting in opacity and information asymmetry that limits the availability of information (Cumming & Johan, 2008a; and 2013; De Clercq et el., 2010; Petersen & Rajan, 1995). Entrepreneurs and founders will have significant knowledge about the startup's future prospects and growth, due to a higher level of involvement in the business, while the external investor is likely to possess more information regarding the marketing and trends in the industry in general. In such

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[9] The Ministry of Commerce and Industry released a notification on April 1, 2015 that defines a startup as "an entity…identified as a startup."

•Up to five years from the date of incorporation.

•If its turnover does not exceed [25 crores] (?) in the last five financial years.

•If it is working towards innovation, development, deployment, and commercialization of new products, processes, or services driven by technology or intellectual property." (Where does this quote begin?)

For this study, we do not have information on turnover, so we use age and technological innovation as the main considerations.

[10] See: Marmer, M., Hermann B.L., & Berman R. (2011). Startup Genome Report 01, A new framework for understanding why startups succeed: http://www.wamda.com/web/uploads/ resources/Startup_Genome_Report.pdf. Accessed 20 April 2013.

cases, when there is a presence of asymmetric information, entrepreneurs may pursue a different strategy than what would be preferred by the investors (Gompers, 2002). It is difficult for investors to monitor ex-post the behavior of entrepreneurs, as entrepreneurs may behave opportunistically after obtaining external financing (Cumming & Johan, 2007; 2008a, 2008b). Additionally, for the investors, it is difficult to ascertain ex-ante the risks and returns of the projects of firms that lack a track record and are developing innovative technologies. For startups, all of these factors create barriers to raising external financing, as they do not have a sufficient track record, credit history, or collateral with which they can use to alleviate such problems (MacMillan et al., 1985; Tyebjee & Bruno, 1984).

Factors that serve to breach the aforementioned barriers have been identified by researchers, the most significant being the founders' human capital (Aspelund et al., 2005; Gimeno et al., 1997; MacMillan et al., 1985; Tyebjee & Bruno, 1984). Human capital theory was initially applied to study the impact of education (Becker, 1964; Schultz, 1961) on economic value. Since then, the theory has been increasingly adopted in the field of entrepreneurship, consistently linking human capital attributes to entrepreneurial success (Unger et al., 2011). The literature on human capital distinguishes three kinds of human capital: generic (general) human capital, firm-specific human capital, and task-specific human capital (Gibbons & Waldman, 2004; Hatch & Dyer, 2004).

While we do not directly distinguish between these particular subcategories of human capital in our paper, we do employ signaling theory to propose how traditional human capital signals (like having prior experience as a startup founder, a technical or software engineer, or a business consultant) and networking signals (such as possessing a degree from an elite educational institute, the breadth of an entrepreneurial team and the number of founders, and the entrepreneurial team's years of experience) serve as quality signals to VCs to both mitigate information asymmetry and enhance the likelihood of access to multiple rounds of financing (Spence, 1973; and 1974). Additionally, we analyze a variable called digital signals, which represents the fan following of the startup on multiple social media sites (Twitter, Facebook, and LinkedIn) (Vismara, 2016). We believe the higher the number of "fan" followings, the more positive the signal of social capital to investors. Even though several empirical studies have analyzed the impact of founders' human capital on firms' growth and performance, there are very few studies that have explored the impact of human capital on access to VC financing in India. Our theoretical model of the signaling impact of these factors is shown in Fig. 1. We consequently developed our hypotheses on the relationship between the founders' human capital and the startups' access to financing followed by our hypothesis on how social media networking can also affect this process of financing.
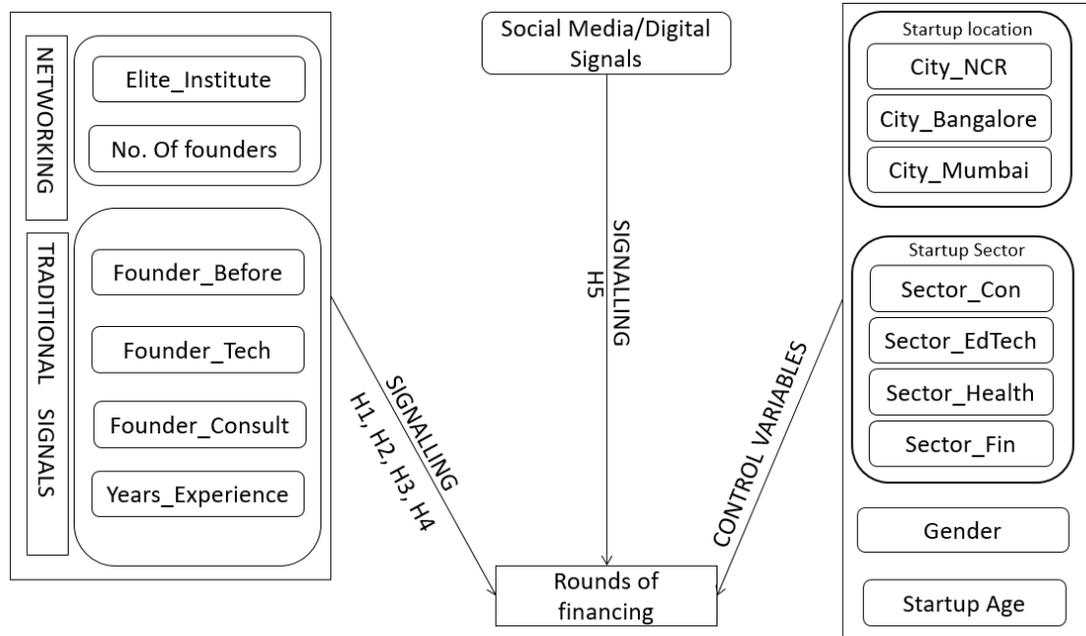
Fig1: Theoretical model showing the relationship of traditional, networking, and social media signals to attract more rounds of financing

2.1 Traditional Signals: Entrepreneurial Experience

Entrepreneurship literature (Baron & Ensley, 2006; Corbett, 2005; McGrath & MacMillan, 2000; Parker, 2006; Ronstadt, 1988; Shane, 2000; Wiklund & Shepherd, 2003) has shown that founders gain significant insight from their past work experiences thereby improving entrepreneurial judgment, greater task performance, and forecasting ability (Clement, 1999; Mikhail et al., 1997). This benefit of experience, generally, may be greater in settings of high uncertainty such as business opportunities in new technology or high-tech industries (Aldrich & Fiol, 1994). However, other scholars argue against the benefit of experience for several reasons, including the heterogeneity across tasks that limits the transfer of gained knowledge (Bonner & Lewis, 1990), cognitive biases that inhibit effective learning (Cassar & Craig, 2009; Hogarth, 1991; Kahneman et al., 1982; Sexton et al. 1997), and the lack of sufficient task repetition to achieve learning by doing (Camerer & Lovallo, 1999). Beyond these theoretical debates, there are crucial practical and policy implications that determine whether or not years of experience do actually impact the entrepreneurship process. However, there is limited empirical evidence from research that directly investigates the role of years of experience on the access to financing for the new startups in this digital age. We believe that experienced entrepreneurs are likely to have a greater understanding of the industry and, given the greater uncertainty for high-tech businesses, the benefit from experience can serve as a positive signal to VCs. Consequently, we posit:

Hypothesis 1: Founders with more work experience are likely to access more rounds of VC financing.

2.1.2 Prior Startup Experience

Studies have shown that investors look for founders with experience (Hall & Hofer, 1993; Kaplan & Stromberg, 2004; Maidique, 1986). Entrepreneurs who have prior experience creating startups develop strong cognitive skills that help them better assess risk (Bar-Hillel, 1983; Hayward et al., 2006) and which, overall, results in a better evaluation and selection of entrepreneurial opportunities (Baron & Ensley, 2006; Gruber et al., 2008). Prior startup founding experience can serve as a powerful human capital signal (Hsu, 2007) and can increase the likelihood of obtaining VC funding. While founders may have been involved in several previous ventures, the frequency and repetition of startup founding experience will not necessarily always serve as a positive signal to investors. In contrast, Beckman et al. (2007) found prior startup experience had an opposite effect on receiving VC funding. Similarly, Baum & Silverman (2004) found that the yearly pre-IPO amount of VC funding obtained by Canadian biotech startups increases with the managerial competencies of a firm's president, while it is negatively related to his or her entrepreneurial experience. Consequently, we posit:

Hypothesis 2a: The prior startup experience of founders facilitates access to more rounds of VC financing.

2.1.3. Prior Technical Experience or Industry Experience

The founders who have had prior industry experience or possess technical skills related to the industry are aware of the industry norms, rules, and dynamics of every changing environment. Such founders with more technical experience and skills are better able to understand the needs of consumers and know how to serve them better (Delmar & Shane, 2006). Founders' industry experience is often viewed positively (Brush et al., 2001) and is valued by potential VCs when making investment decisions (MacMillan et al., 1985). Eckhardt et al., (2006) also find similar results, where prior industry-specific experiences positively influence the likelihood of obtaining external financing. This can serve as a positive signal to investors who believe that industrial experience can serve them better. Consequently, we posit:

Hypothesis 2b: The prior technical experience of founders facilitates access to more rounds of financing through VC.

2.1.4 Prior Business Consultancy Experience

The role of an expert consultant has increasingly become significant for firms seeking to be successful. An event study by Bergh & Gibbons (2011) that analyses firms that announced the hiring of

consultants finds that the stock market, on average, responded positively and significantly to the announcement. There is, however, not much literature on the impact of prior business consultancy experience on the success of the venture or in obtaining successful VC financing. From our data, business consultancy appeared as the third most significant experience a founder should possess, which thus made us consider that a founder's prior experience as a business consultant serves as a relevant signal to VCs. We believe that business consultants better understand the dynamics of the new industry, as they often consult projects that are short and cyclical in nature. They also have the skills to quickly understand the market requirements and market demands for their products. Additionally, they possess project management skills, are used to working under strict deadlines, and must master communication skills early in their careers, as they must often address the top executives of the companies. All these skills can be effectively used during new venture creation. Business consultants also know how to perform strategic, operational, and financial analyses for their clients. The above justifications lead to the following hypothesis:

Hypothesis 2c: Prior business consultancy experience of founders facilitates access to more rounds of VC financing.

2.2. Networking Signals

Extant literature defines a social network as a "web of personal connections and relationships for the purpose of securing favors in personal and/or organizational action" (Adler & Kwon, 2002; Burt, 1997; Granovetter, 1985; Groh & Wallmeroth, 2016). Members of social networks are better able to access and exchange new knowledge, thus facilitating knowledge creation. In firms or organizational settings, social networks may involve relationships among individuals in a formal structure of business connections. For the purposes of our paper, we focus on social networks as an informal structure of personal relations bound by institutional space (Sorenson, 2003). We look to the quality of the network as certified by a degree from an elite educational system which not only legitimizes quality but also enables access to equally successful alumni. The extent of the network is measured by the size of the entrepreneurial team.

2.2.1. A Degree From an Elite Educational Institute

A degree from an elite educational institute is perceived as a quality signal. Engel & Keilbach (2007), using a sample of mostly private Germans firms, found that the education of the founders significantly influences the likelihood of receiving VC. Maidique (1986) established that VCs considered founders with advanced degrees from high-quality institutions to affect their startup success. Conversely, Audretsch & Lehmann (2004), employing a sample of 341 German startups listed in the Neuer Markt,

highlighted that the number of members of a firm's top management team with a Ph.D. degree had no impact on access to VC. Thus, the existing literature on this topic is quite inconclusive. Whilst most of the extant knowledge has been derived from and relevant to developed economies, the situation in developing economies still remains an open question. How does networking capital help the entrepreneur raise financing for a startup based in India? In particular, we are interested in knowing whether or not graduating from an elite educational institute increases the likelihood of financing compared to graduating from other non-elite educational institutes. We base our assertion on the fact that degrees from recognized elite institutes serves not only as a credibility signal to VCs in comparison to those who graduate from non-elite institutes but also signals that, throughout the time spent in higher education, a useful network of equally successful elites is established in an informal manner. Following this assertion, we build upon our first hypotheses:

Hypothesis 3: Indian startup founders with degrees from elite educational institutes are likely to attract more rounds of VC financing.

2.2.2. The Entrepreneurial Team (The Number of Founders)

Gartner et al. (1994) made the argument that the entrepreneur in entrepreneurship is typically plural, not singular. Growing literature (Ensley et al., 1998; ; Gartner et al., 1994; Lechler, 2001; Reich, 1987) on this topic has established the fact that the activities involved in establishing and growing a new venture are more often taken by entrepreneurial teams rather than by a solitary entrepreneur. By pooling founder's talents, teams can resolve complex problems (Eisenhardt & Schoonhoven, 1990; Hambrick & D'Aveni, 1992). Entrepreneurial teams are more likely to attract financial resources such as VC and traditional capital through banks (Beckman et al., 2007; Cooper & Daily, 1997). The size of the entrepreneurial team has been reported to have a positive association with venture performance in a variety of settings, as larger teams are likely to have more resources (Colombo & Grilli, 2005; Cooper & Bruno, 1977; Eisenhardt & Schoonhoven, 1990; Feeser & Willard, 1990; Haleblian & Finkelstein, 1993). We believe that a higher number of founders on the entrepreneurial team is beneficial as well in the context of India, where the startup ecosystem is not so friendly for new ventures and involves a lot of bureaucracy and administrative burden. Having a team of co-founders with complementary skill sets not only helps in sharing the burden of work but also enables startup access to the numerous co-founders' networks. Accordingly, we expect that a higher number of founders should increase the startup's social network capital. Consequently, we posit:

Hypothesis 4: Indian startups that have more founders in their entrepreneurial team are likely to attract more rounds of VC financing

2.3 The Strength of Social Networking as a Digital Signal

Podolny (2005) has proposed that "the greater market participants' uncertainty about the underlying quality of a producer and the producer's product, the more that market participants will rely on the producer's status to make inferences about quality." Startups can effectively use social media as a crucial medium not only for the exchange of information with clients but also to reduce information scarcity problems that exist between startups and investors. A startup's social media presence and fan following could demonstrate the startup's ability to lure consumers, strengthen its brand, and engage and retain consumers (Vismara, 2016). This, in turn, can serve as a positive signal to VCs and increase the likelihood of securing funding. Taken broadly, existing studies suggest (Goh et al., 2013; Luo et al., 2013) that the use of social media can influence overall firm performance, including the success of early-stage firms and their ability to obtain financing. While these studies mostly use data from established companies, we expect to see a similar logic at work for startup firms. With respect to signaling function, social networking may also serve as legitimization for the startup idea/product or process and, consequently, may facilitate the acquisition of financial capital. Thus, we posit:

Hypothesis 5: Startups that have more followers (fans) on social media (Twitter/Facebook/LinkedIn) are more likely to receive more rounds of VC financing.

3. EMPIRICAL STRATEGY

3.1. Data Collection

We collected data comprising 47 active startups and 55 failed startups from 2014–2017 through several online sources and random searches (Crunchbase[11], Traxn[12], Trak.in[13], Inc42[14] and Internet

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[11] Crunchbase is an online database of startups and technological companies around the globe. The database provides information related to funding rounds. We used the paid version, Crunchbase Pro, which allowed access to data pertaining to Indian startups and their investment details. Crunchbase can be used by entrepreneurs, business analysts, researchers, and investors. https://www.crunchbase.com/.

[12] Traxn is a database providing information on nearly 10 million companies around the globe. It is a paid database considered to be very accurate and precise. https://tracxn.com/.

[13] Trak.in is an Indian blog that list the startup by years. Information, such as the names of startups that have utilized venture capital funding, is available. https://trak.in/Tags/Business/category/startup/.

[14] Inc.42 is a leading Indian media and information platform that is known for its coverage of Indian startup ecosystems. It publishes several reports and articles that offer information on startups that have filed for bankruptcies. This is a very useful platform for accessing information on Indian startups. https://inc42.com/.

specified word-based searches[15]). The Indian VC industry has passed through three distinct phases in the last decade: the growth stage, maturation and moderation, and renewed optimism. We analyzed data from 2014-2017, as these years were marked with heavy investments in Indian startups, and, more specifically, with higher quality investments in digital startups. We included failed startups to avoid survivorship bias in our sample. T-tests indicated no significant differences between the 102 active startups and failed ones in terms of age, sector, and city. We selected only the technological startups in the domains of Consumer Internet services, Fintech, business analytics, Edtech, Foodtech, Healthtech, Logistics, and Enterprise Applications. We collected information related to total funds raised and multiple rounds of financing through the Crunchbase database, and we cross-checked the results with Traxn and with online media reports (Trak.in and Inc42) to check the accuracy of the data. We were also able to obtain information on the names of founders, which we then used on LinkedIn to collect more information related to human capital variables, such as previous experience (number of years of experience and kind of prior experience), educational institution, and gender. We then collected information related to the strength of the social media network of funded startups through LinkedIn, Facebook, and Twitter and added a combined variable of the total number of fan followers. We also collected information on the region of the startup, the year of launch, and the sector. A detailed analysis of the variables and from where they were collected is provided in the appendix (A1). Data collection ended in July 2018, therefore any data after that date go beyond the scope of our study.

3.1.1. Dependent Variables

To test the independent effects of human capital and social networking on access to financing, we use rounds of financing (FIN_ROUNDS)[16] as our dependent variable. Based on the data collected for both active startups and failed startups, we found that only one startup was funded through debt. All of the other startups were funded initially through VC and, later, funded through both VC and private equity. We collected the information on the number of financing rounds starting from seed funding through to the last funding round as of July 2018, for both kinds of firms. We found that while the average round of funding received by successful firms was 3, for failed firms it was only 1. We also collected information on the total amount of financing raised as of July 2018. The average funding amount for the still-active startups was

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[15] We searched for specific words like "technological startups from India," "emerging startups," "failed startups," and so forth to build our database of 102 startups. We use random searches so data does not come from one Internet platform.

[16] Indian startups can be financed in stages. The process begins from the seed stage, which is the first level of raising capital, solely given on a concept or idea. Early stage investing is identified within Series A and Series B of financing rounds and is associated with the early stage and growth. The next round of financing is associated with expansion.

around US$300 million, whereas for failed firms it was $4 million. We needed to consider that in the case of failed startups, the details of the amount raised were absent for 20 startups. Being unable to utilize the amount of funding as the dependent variable, we employed rounds of financing. Only VC and private equity funds are included in our data sample and we do not include funds provided by the government or the founders.

3.1.2. Independent Variables

3.1.2.1. Founders' Human and Networking Capital

We argue that the founders' human capital, particularly their years of prior experience and prior relevant experience—industry-related prior experience, previous founding experience, previous business consultancy experience, an educational degree from elite institute[17], and the presence of an entrepreneurial team, rather than being a solo entrepreneur—sends signals about the quality of the founding members' productivity and effectiveness to VCs. We treat these types of human capital separately.

We include an independent variable related to the total years of average experience (YEARS_EXP) of the founder and also included dummy variables related to relevant prior experience. Our descriptive statistics show that out of 214 founders, 36% of the founders have had prior experience as a founder, 21% have had prior experience as a software engineer, and 15% have had prior experience as a business consultant. The other 28% have had other prior experiences related to accounting, investing, and advocating, or have worked as a scientist or product and marketing manager. Consequently, we believe these skills (prior founder, prior technical, and prior business consultant) are significant for startups and help them to access financing. As such, we created dummy variables related to relevant experience: at least one founder has prior technical experience (ATLEAST_PRIORTECH_EXP), at least one founder has prior founding experience (ATLEAST_PRIORFOUNDER_EXP), and at least one founder has prior business consultant experience (ATLEAST_PRIORCONSULT_EXP) (Gimmon & Levie, 2010; Hsu, 2007). A degree from IIT, IIM, BITS, and foreign universities that are recognized elite institutes (DEG_ELITE) is a dummy variable that takes a value of 1, and 0 otherwise. Out of the 214 founders in our data sample, nearly 83% of them attended IIT, IIM, BITS PILANI, or an elite foreign university, and the rest attended other

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[17] According to our data sample, 73% of the founders came from the Indian Institute of Technology (IITs), the Indian Institute of Management (IIM), the Birla Institute of Technology and Science (BITS) Pilani, or a foreign university like Harvard, Stanford, The Kellogg School of Management at Northwestern University, etc. We refer to reputable rankings that regard these as elite educational institutes. For example, Outlook magazine regards IITs and BITS as the top-ranked Engineering colleges in India: https://www.outlookindia.com/magazine/story/top-100-engineering-colleges-in-2018/300176. The Indian Institute of Management is the top Business Management school in India: https://www.outlookindia.com/magazine/story/outlook-drshti-survey-top-100-b-schools-in-india/300668.

educational institutes in India. As such, we believe attendance at one of these institutes should result in better access to financing rounds.

We include an entrepreneurial team as depicted by the variable number of founders (NO_OF_FOUNDERS). The presence of an entrepreneurial team has been shown to positively impact venture performance (Colombo & Grilli, 2005; Cooper & Bruno, 1977; Eisenhardt & Schoonhoven, 1990; Feeser & Willard, 1990; Haleblian & Finkelstein, 1993). Our descriptive statistics present only 24 solo entrepreneurs; in this regard, we consider this an important variable that impacts access to financing.

3.1.2.2. Social Networking

We include variable social networking (SOCIAL_NETWORK) to determine the impact of social networking, or digital signals as represented by the number of fan followers, on multiple social media sites with access to financing. The social networking variable takes value from the social media sites of each startup, such as Twitter (the number of followers), LinkedIn (the number of connections), and Facebook (the number of fans). We add them all together to determine the strength of their digital networking. The average number of connections for active startups is around 218,870 and for failed startups is only 72,380. We believe that founders of failed startups were not able to gather strength on their social media profiles, which could have been interpreted as a negative digital signal by the investors. We believe that social media strength plays a very important role for not only creating brand awareness or marketing products but also to gain traction and help access subsequent rounds of financing.

3.1.3. Control variables

We controlled for certain variables that might impact the rounds of financing. First, we controlled for geographic location (Blau, 1977; Sorenson & Stuart, 2001) to account for spatial proximity to VCs (Gompers & Lerner, 1999; Sorenson & Stuart, 2001). Geographical distribution of these startups, according to the data, was as follows: 26 are located in Bangalore, 47 in the Northern Capital Region (NCR), 16 in Mumbai, and the remainder in other cities in India. Consequently, we coded this variable 1 for startups located in premium cities for investments (e.g., Bangalore, NCR, and Mumbai) (Florida & Kenney, 1988; Chatterji et al., 2014) and 0 for ventures located in other areas. We have three dummy variables: City_Bangalore, City_NCR, and City_Mumbai. These cities are of strategic importance, as Bangalore is known as the Silicon Valley of India and home to many technology startups; Mumbai is known as the financial capital and home to many fintechs; and the NCR region is also developing into a home to many new technology startups. Second, we controlled for the age of the startup, as investors may prefer to invest in more established startups that have established market positions (Hsu, 2007; Shane & Stuart, 2002). Finally, we control for industry, by creating dummy variables for industry based on our descriptive

statistics. The following dummy variables represent the different sectors of technology startups: consumer internet (CONSUMER_INTERNET), healthtech (HEALTHTECH), edtech (EDTECH), and fintech (FINTECH). Additional control variables related to founder's gender was also included in the regression model, as our descriptive statistics suggest a huge gender bias, where women only represent 8 percent of 214 founders. The detailed descriptive statistics are provided in Table 2. To avoid biased results given different units of measurement applying to variables, all variables were normalized except the dummy controls.

3.2. Methodology

We used SPSS statistical software to test the main empirical hypotheses discussed in the previous sections; this section includes two steps. First, we estimated a regression model to predict the number of financing rounds (FIN_ROUNDS) as a function of the various independent variables and control variables discussed earlier. *Post hoc* multicollinearity diagnostics indicated variance inflation factors (VIFs) well below the threshold of 5 for all the independent variables tested. However, for rigor and robustness, based on the observed correlation matrix, we also ran structural equation modelling (SEM) with explicit covariance paths for all *a priori* statistically significant correlations (observed and expected) between the independent variables. This ability of SEM to explicitly handle multicollinearity is one of its important advantages compared to traditional ordinary least square (OLS) multiple regression.

Based on the hypothetical factors that could explain the number of financing rounds of startups in India, our multiple regression model (Model 1) contains all the independent variables of the study to test for the predicted signal. It is as follows:

(1) $FIN\_ROUNDS_i = \beta_0 + \beta_1 SOCIAL\_NETWORK_i + \beta_2 AGE_i + \beta_3 NO\_OF\_FOUNDERS_i + \beta_4 YEARS\_EXP_i + \beta_5 DEG\_ELITE_i + \beta_6 ATLEAST\_PRIORFOUNDER\_EXP_i + \beta_7 ATLEAST\_PRIORTECH\_EXP_i + \beta_8 ATLEAST\_PRIORCONSULT\_EXP_i + \beta_9 GENDER_i + \beta_{10} CONSUMER\_INTERNET_i + \beta_{11} EDTECH_i + \beta_{12} HEALTHTECH_i + \beta_{13} FINTECH_i + \beta_{14} CITY\_NCR_i + \beta_{15} CITY\_BANGALORE_i + \beta_{16} CITY\_MUMBAI_i + \varepsilon_{i.,}$

To further understand the relative contributions of the various predictors, we also ran 4 more regression models. Model 2 excluded the variable SOCIAL_NETWORK, Model 3 excluded NO_OF_FOUNDERS, Model 4 excluded DEG_ELITE, and Model 5 excluded all control variables to observe whether or not these variables could potentially mask the effects of other variables in the original model.

3.2.1. Supplementary Analyses for Robustness and Cross-Validation

We empirically tackled the theoretical model presented in Fig. 1 using structural equation modelling (SEM) as a robustness test. As mentioned earlier, the advantage of using SEM instead of the combination of aggregate scores from the factor analysis and traditional regression models with multiple inputs is that a) it allows for explicit handling of multicollinearity through covariance paths, unlike multiple regressions, and b) measurement error is not aggregated in a residual error term. Further the evaluation of the models is based on a diverse set of fit indices including absolute, relative, and comparative fit indices as well as information like the Akaike Information Criterion and the Bayesian Information Criterion. One common rule-of-thumb for implementing SEM is that it should have an *a priori* minimum threshold of 100 subjects (Williams et al., 2004) and a *post hoc* Hoelter's N of 75-200; our sample meets these thresholds: (n=102; Hoelter's N = 139 (95% confidence) and 152 (99% confidence). Unstandardized and standardized coefficients estimates are presented in the following Results section in order to allow multiple perspective comparisons with the conventional regression model, as well as to compare relative contributions (effect sizes) of the various independent and control variables.

4. RESULTS

Table 1 and Table 2 reports the bivariate correlations and descriptive statistics, respectively, for the variables in the analysis. Significant correlations were found between the dependent variable and the explanatory variables "Educational Institute," "Number of Founders," and "Social Network." Correlation analysis results indicate weak levels (<.3) of correlations between all independent variables except "Educational Institute" and "Prior founder experience," where we observe strong significant correlation (0.340). Further, we examined multicollinearity using variance inflation factors (VIF). The general rule of thumb is that VIFs exceeding 10 are a sign of serious multicollinearity. The VIF value for all studied variables is < 3.0 (maximum value of 2,972), suggesting that multicollinearity is not a major concern (Hair et al., 2010). A strong negative and significant correlation was found between sector and city control variables. To eliminate possible collinearity problems and more than verify the VIF values, we performed a robustness test using structured equation modelling (SEM).

Table1: Nonparametric correlations - Kendall's tau_b (1 dependent and 16 independent variables, 2-tailed)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	N Financing rounds	1.00																
2	Educational Institute	.223*	1.00															
3	Number of Founders	.240**	.187*	1.00														
4	Years of Experience	.126	-.053	-.005	1.00													
5	Prior tech experience	.163	.187	.270**	-.067	1.00												
6	Prior founder experience	.139	.340**	.232*	.064	.117	1.00											
7	Prior Consultant experience	.074	.087	.153	.012	.064	.087	1.00										
8	Age	.121	.093	.063	.187**	.039	.159	.144	1.00									
9	Social Network	.357**	.013	.071	.116	-.020	-.074	.124	.125	1.00								
10	Gender	.058	.089	.012	-.084	.144	.109	-.030	.007	-.101	1.00							
11	City Bangalore	.079	.102	.051	.056	.201*	.148	.054	.016	-.032	.035	1.00						
12	City NCR	-.004	.065	.040	.044	-.061	-.047	.031	.026	-.047	.015	-.541**	1.00					
13	City Mumbai	-.039	.093	.021	-.024	-.054	.042	-.051	-.090	.045	-.012	-.252*	-.399**	1.00				
14	Consumer Internet	.031	.091	.026	.108	-.056	-.082	-.010	-.081	.031	.083	-.242*	.214*	-.077	1.00			
15	Fintech	-.039	.085	.107	.005	.046	.204*	.170	.141	.064	-.037	.056	-.080	.056	-.372**	1.00		
16	HealthTech	.006	-.090	-.176	.076	-.074	-.118	-.193	.119	.060	-.056	.080	-.123	-.026	-.349**	-.091	1.00	
17	Ed tech	-.033	.038	.053	-.013	.031	.222*	-.095	.059	.060	-.078	.019	-.095	.203*	-.324**	-.084	-.079	1.00

Due to the binary nature of some variables, these correlations should be interpreted with care.

Kendall's correlations are significant at *p < .05, **p < .01, n = 102

Table 2: Descriptive statistics related to active vs. failed startups

	Total Mean	Active Startups Mean	Failed Startups Mean
Rounds of Financing	1.82 (1.28)	2.34 (1.55)	1.38 (0.76)
Average Funding		300, 062,191	4, 678,571
Elite Educational Institute	73%	74%	58%
Other Educational Institutes	27%	26%	42%
Prior Technical Experience	21%	20%	21%
Prior Founders Experience	36%	38%	32%
Prior Consultants Experience	15%	15%	16%
Other Prior Experiences	28%	27%	29%
Years of Experience	12.01 (5.92)	12.93 (5.03)	11.22 (6.54)
Average no. of founders	2.10 (1.08)	2,32 (1.27)	1.91 (0.84)
Bangalore	25%	34%	18%
NCR	46%	38%	53%
Mumbai	16%	15%	16%
Other cities	13%	13%	13%
Male founders	92%	95%	88%
Female founders	8%	5%	12%
Consumer Internet	59%	45%	71%
Fintech	9%	13%	5%
Healthtech	8%	15%	2%
Edtech	7%	13%	2%
Others	17%	16%	20%

Note: Standard deviation in parentheses. Total n = 102; Active n = 47; Failed n = 55.

The main results of our regressions analysis are summarized in Table 3. Table 3 displays the unstandardized coefficients (beta and standard error), the standardized beta and sig., the number of observations, the F and sig., and the R^2 and adjusted R^2 for each model.

These analyses (ANOVA) resulted in 4 statistically significant models (Models 1, 3, 4, and 5). Model 1 is the model that includes all variables [$F_{(16,85)} = 2,728$; $p < 0.002$; $R^2 = 0.339$]. The independent variables SOCIAL_NETWORK ($\beta = 0.469$; $t = 4.907$; $p < 0.001$), NO_OF_FOUNDERS ($\beta = 0.280$; $t = 2.821$; $p < 0.006$), and DEG_ELITE ($\beta = 0.216$; $t = 2.086$; $p < 0.040$) predicted the FIN_ROUNDS. This model allowed us to test our hypotheses (H1–H5). We used the other models to ensure that significant independent variables were not masking the effect of other ones.

We find that the educational institute, the number of founders, and the social network has a positive significant effect for all significant models. Given the fact that the coefficient for the social network was highly significant for all models, we ran additional models excluding this variable to test the robustness of Model 1. This analysis suggested a drop of the explanatory power of all models, as indicated by R^2; however, three models still remained significant (Prob > F: < 0.05) and did not impact our final conclusion in any manner. However, Model 2, the model without the "SOCIAL_NETWORK" variable is not significant, and the adjusted R^2 is almost irrelevant (0.004). This suggests that this variable "SOCIAL_NETWORK" is an important predictor of access to VC financing for Indian startups. Our results support other studies that find the use of social media can influence overall firm performance, including the success of early-stage firms and their ability to obtain financing (Goh et al., 2013; Luo et al., 2013). Furthermore, it was found that the number of founders "NO_OF_FOUNDERS" tends to have significantly higher levels of influence in the number of finance rounds. This result also supports previous research that finds larger teams are likely to have access to more resources (Colombo & Grilli, 2005; Cooper & Bruno, 1977; Eisenhardt & Schoonhoven, 1990; Feeser & Willard, 1990; Haleblian & Finkelstein, 1993).

Table 3: Regression analysis results (Models 1– 5)

Variables	Model 1			Model 2			Model 3			Model 4			Model 5			expected sign
	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	
Educational Institute	0.574* (0.275)	0.216	0.040	0.422 (0.308)	0.159	0.174	0.602* (0.286)	0.226	0.038				0.469+ (0.248)	0.176	0.062	+ H1
Number of Founders	0.332** (0.118)	0.280	0.006	0.330* (0.133)	0.278	0.015				0.341** (0.120)	0.287	0.006	0.318** (0.113)	0.268	0.006	+ H2
Years of Experience	0.008 (0.021)	0.039	0.695	0.018 (0.024)	0.083	0.454	0.008 (0.022)	0.039	0.703	0.002 (0.021)	0.008	0.936	0.002 (0.019)	0.009	0.922	+ H3
Prior technical exp	-0.029 (0.261)	-0.011	0.912	0.224 (0.288)	0.085	0.438	0.171 (0.261)	0.065	0.514	0.038 (0.264)	0.015	0.885	0.006 (0.244)	0.002	0.979	+ H4b
Prior founder exp	0.186 (0.263)	0.073	0.481	0.115 (0.295)	0.045	0.698	0.312 (0.269)	0.122	0.250	0.321 (0.259)	0.126	0.219	0.143 (0.239)	0.056	0.551	+ H4a
Prior consultant exp	-0.210 (0.265)	-0.076	0.430	-0.069 (0.297)	-0.025	0.816	-0.092 (0.272)	-0.033	0.737	-0.188 (0.270)	-0.068	0.487	-0.245 (0.245)	-0.089	0.319	+ H4c
Age	-0.021 (0.056)	-0.037	0.708	0.012 (0.063)	0.022	0.845	-0.013 (0.058)	-0.023	0.822	-0.011 (0.057)	-0.019	0.848				+
Social Network	0.000*** (0.000)	0.469	0.000				0.000*** (0.000)	0.468	0.000	0.000*** (0.000)	0.446	0.000	0.000*** (0.000)	0.434	0.000	+ H5
Gender	0.399 (0.310)	0.120	0.202	0.061 (0.341)	0.018	0.857	0.380 (0.323)	0.114	0.242	0.394 (0.316)	0.118	0.217				?
City Bangalore	-0.491 (0.442)	-0.169	0.270	-0.337 (0.497)	-0.116	0.499	-0.459 (0.460)	-0.157	0.321	-0.208 (0.429)	-0.071	0.630				+
City NCR	-0.386 (0.388)	-0.151	0.322	-0.298 (0.436)	-0.117	0.497	-0.296 (0.402)	-0.116	0.463	-0.139 (0.376)	-0.055	0.712				+
City Mumbai	-0.475 (0.467)	-0.136	0.312	-0.360 (0.526)	-0.103	0.496	-0.422 (0.485)	-0.121	0.387	-0.175 (0.453)	-0.050	0.700				+
Consumer Internet	-0.111 (0.335)	-0.043	0.742	-0.077 (0.377)	-0.030	0.838	-0.044 (0.347)	-0.017	0.899	0.040 (0.333)	0.015	0.906				+

Table 3 (continued)

Variables	Model 1			Model 2			Model 3			Model 4			Model 5			expected sign
	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	Unst. β	St. β	Sig.	
Fintech	-0.317 (0.494)	-0.071	0.523	-0.491 (0.555)	-0.110	0.379	-0.212 (0.512)	-0.047	0.680	-0.226 (0.502)	-0.050	0.654				+
HealthTech	-0.075 (0.510)	-0.016	0.883	-0.050 (0.574)	-0.011	0.930	-0.126 (0.530)	-0.027	0.813	0.019 (0.518)	0.004	0.971				+
Edtech	-0.141 (0.542)	-0.028	0.796	-0.003 (0.610)	-0.001	0.996	-0.079 (0.563)	-0.016	0.889	-0.103 (0.552)	-0.021	0.852				+
Constant	0.650 (0.543)		0.235	0.803 (0.610)		0.192	1.039 (0.546)		0.060	0.627 (0.553)		0.261	0.620 (0.346)		0.077	
F	2.728			1.028			2.201			2.521			6.060			
Prob > F	0.002			0.435			0.012			0.004			0.000			
R2	0.339			0.152			0.277			0.305			0.311			
Adjusted R2	0.215			0.004			0.151			0.184			0.260			

Notes: Non-standardized regression betas presented. Standard errors in parentheses. n = 102
Unst. β – Unstandardized Beta; St. β – Standardized Beta; Sig. - *p-value*
***p<.001; ** p<.01; * p<.05; +p<.10

Surprisingly, our analysis indicates that exploratory variables related to the traditional signals of founder experience (the number of years or the type of prior experience) do not have significant impact on the number of financing rounds. This is contrary to prior research that finds founders' industry experience to be valued (Brush et al., 2001), especially by VCs in making investment decisions (MacMillan et al., 1985). We believe for investors in developing economies where institutions are arguably weaker, informal quality signals may be much more important to mitigate information asymmetry. It is therefore possible that investors in new technology startups in India may place more value on networking and digital signals than traditional human capital signals.

4.1 Results on Hypothesized Effects

Here, we summarize the hypotheses test results, reported in Table 3. We used Model 1 to discuss our findings for the hypothesized main effects. All our hypotheses are directional. Our first 6 hypotheses are related to human capital and networks, and the last one to the strength of social or digital networking.

H1 – not supported. Experienced founders are likely to access more rounds of VC financing. The number of years of experience a founder has is not significant in the access to financial capital through VCs.

H2a – not supported. Founders who have prior startup experience are likely to access more rounds of VC financing. Prior startup experience of a founder is not significant in the access to financial capital through VCs.

H2b – not supported. Technically experienced founders are likely to access more rounds of VC financing. Prior technical experience of a founder is not significant in the access to financial capital through VCs.

H2c – not supported. Founders with prior business consultancy experience are likely to access more rounds of VC financing. Prior business consultancy of a founder is not significant in the access to financial capital through VCs.

H3 – supported. Indian startups founders who obtain a degree from an elite educational institute are likely to attract more rounds of financing (Beta = 0.574, p < 0.01). We find that the educational institute has a significant positive impact on the number of financing rounds.

H4 – supported. Indian startups that have more founders in their entrepreneurial team are likely to attract more rounds of financing (Beta = 0.332, p < 0.01). In line with previous research, we find that the number of founders has a significant positive impact on the number of financing rounds for Indian startups.

This last hypothesis is related to social media networking.

H5 – supported. Startups that have more followers (fans) on social media (Twitter/Facebook/LinkedIn) are more likely to receive more rounds of financing from investors (Beta = 0.000, p < 0.001). In accordance with previous studies, the social network has a significant positive impact on the number of financing rounds.

4.2 Robustness test

We show in Figure 1 the general study model, including the major constructs of "human capital" and "social capital" together with the control variables. In our structured equation model, we present all variables that directly relate to the number of financing rounds. In general, we are able to verifiy that the relationship between the variables educational institute "DEG_ELITE," the number of founders "NO_OF_FOUNDERS," and social capital "SOCIAL_NETWORK" with financing rounds "FIN_ROUNDS" is significant (see Table 4). The high levels of association indicate that these three variables influence the number of financing rounds. The SEM results presented a Chi² (95) = 86.543, a practical significance = 0.720, R^2 = 0.360.

Table 4: Regression Weights: Unstandardized, Standardized, and Significance Levels for Models in Figure 1 (Standard Errors in Parentheses; n = 102)

			Unst. β		St. β	Sig.
Fin_Rounds	<--	Social_Network	0.000***	(0.000)	0.461	0.000***
Fin_Rounds	<--	No_of_Founders	0.332**	(0.106)	0.272	0.002
Fin_Rounds	<--	City_Bangalore	-0.491	(0.383)	-0.166	0.200
Fin_Rounds	<--	City_NCR	-0.386	(0.339)	-0.149	0.255
Fin_Rounds	<--	City_Mumbai	-0.475	(0.412)	-0.133	0.248
Fin_Rounds	<--	Age	-0.021	(0.047)	-0.037	0.654
Fin_Rounds	<--	Gender	0.399	(0.270)	0.118	0.139
Fin_Rounds	<--	EdTech	-0.141	(0.481)	-0.027	0.770
Fin_Rounds	<--	HealthTech	-0.075	(0.439)	-0.016	0.864
Fin_Rounds	<--	Consumer_Internet	-0.111	(0.289)	-0.042	0.701
Fin_Rounds	<--	FinTech	-0.317	(0.434)	-0.069	0.465
Fin_Rounds	<--	Years_Exp	0.008	(0.018)	0.038	0.643
Fin_Rounds	<--	Deg_Elite	0.574*	(0.241)	0.209	0.017
Fin_Rounds	<--	Atleast_PriorFounder_Exp	0.186	(0.230)	0.071	0.418
Fin_Rounds	<--	Atleast_PriorTech_Exp	-0.029	(0.223)	-0.011	0.897
Fin_Rounds	<--	Atleast_PriorConsult_Exp	-0.210	(0.228)	-0.075	0.357

Note: χ^2 (95) = 86.543; CFI > 0.95; RMSEA < 0.05; ***p<.001; ** p<.01; * p<.05; +p<.10
Unst. β – Unstandardized Beta; St. β – Standardized Beta; Sig. - *p-value*

5. CONCLUSION AND LIMITATION OF RESEARCH

VCs confronted with information asymmetry are likely to look for certain signals to reduce informational gaps in the exercise of their judgement. This leads to the question, if information asymmetry is potentially heightened due to the continuously evolving nature of digital startups or the higher institutional burdens in certain countries, how would this affect the signals? We believe our research

contributes to extant literature as we link signaling theory to traditional human capital, networking, and social media networking in the context of the acquisition of VC funding by technology startups in a developing country with higher institutional burdens (Podolny, 1993, and 1994, and 2005; Spence, 1974). We build five main hypotheses (H1–H5). Our findings contain a series of larger implications for entrepreneurs, investors, and policy makers. To begin, our results suggest that traditional human capital factors may not necessarily serve as quality signals for technology startups in India, and other measures of entrepreneurial quality, such as quality of networks (networking signals) and social media networking (digital signals) may serve as better quality signals to access financing. The empirical analysis highlights the following main results. The first two main results are related to the role of traditional human capital in the funding of startups, in particular the work experience of the founder. Our empirical results suggest that years of experience do not impact the access of financing of a startup and neither do prior relevant experiences (as a founder, as a software engineer, or as a business consultant). A degree from an elite educational institute and the breadth of the entrepreneurial team are positively associated with the likelihood of access to financing. The third main result is related to the strength of social media networking on the studied startups. This result makes an important contribution to the signaling literature (as most of the current literature focuses on the developed nations of the US and Europe), especially from the perspective of emerging economies, since our study provides support for the changing importance of signals over time in the context of acquisition of VC financing and in the virtual world, where the impact of social media cannot be excluded. Indeed, out of all the digital signals, social media networking has the strongest impact on access to funding.

When interpreting the results of our study, certain limitations need to be kept in mind. First, we have tested the impact of traditional human capital factors, networking, and social media networking on access to the financing of startups. However, in the actual decision-making process, certain other factors related to revenue growth rates or estimated market size or information about patents may play a role as well. Information for failed startups is absent. Second, our study is focused on India, and similar research on other emerging countries should be considered on topic. Third, we investigate the relationship between signal and financial resource acquisition and adopt a static approach (Elitzur & Gavious, 2003; Higgins & Gulati, 2006). While our study provides important insights, finance acquisition is not a static process but rather a continuous process where different signals can play a different role at different stages. Some signals will be relevant for some stages but become irrelevant in subsequent stages. Thus, it would be interesting to develop a model that tests how different signals help the startup to acquire resources during different stages. Fourth, the study is mainly quantitative and lacks a qualitative view from investors as to what makes a strong signal during the financing rounds. Thus, we encourage future research that can consider integrating both qualitative and quantitative variables so that more understanding can be propounded into

the contingencies that enhance the financing of startups. Fifth, the validity and authenticity of the data are limited to what we have collected from multiple databases such as Traxn, Crunchbase, Techinasia, LinkedIn, Twitter, and Facebook. Even though we have sought to verify the information collected, there may still be a chance of some discrepancies, which cannot be avoided. Lastly, even though we establish causality relationships through our study, our work was done to support a set of postulated hypotheses; it may not imply or establish a causal relationship.

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A1: Description of variables

Variable Definitions

Dependent Variables

Variable Name	Description
FIN_ROUNDS	Multiple rounds of financing received by startups to July 2018. This is a continuous variable. We obtained these data from Crunchbase, Traxn, and Techinasia

Independent Variables Related to Human Capital

Variable Name	Description
DEG_ELITE	Dummy variable that takes the value 1 if at least one of the founders obtained an educational degree from an elite educational institute (top ranked from India and abroad) and 0 otherwise. We obtained these data from LinkedIn.
NO_OF_FOUNDERS	Shows the number of founders for the startups in the sample. This is a continuous variable. We obtained this information from Crunchbase, Traxn, and Techinasia.
YEARS_EXP	The average number of years of experience before starting the startup concerned. We obtained this information from LinkedIn.
ATLEAST_PRIORFOUNDER_EXP	Dummy variable that takes the value of 1 if at least one of the founders has had prior experience as the founder and 0 otherwise. We obtained this information from LinkedIn.
ATLEAST_PRIORTECH_EXP	Dummy variable that takes the value of 1 if at least one of the founders has had prior experience as a technical engineer (software) and 0 otherwise. We obtained this information from LinkedIn.
ATLEAST_PRIORCONSULT_EXP	Dummy variable that takes the value of 1 if at least one of the founders has had prior experience as a business consultant and otherwise 0. We obtained this information from LinkedIn.

Independent Variables Related to Social Media Networking

Variable Name	Description
SOCIAL_NETWORK	This variable compiles the number fans following startups on multiple social media platforms

(LinkedIn+Twitter+Facebook). Information was obtained from the respective websites.

Control Variables

Variable Name	Description
CITY_BANGALORE	Dummy variable that takes a value of 1 if the location of the startup is in Bangalore and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
CITY_NCR	Dummy variable that takes a value of 1 if the location of the startup is in NCR and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
CITY_MUMBAI	Dummy variable that takes a value of 1 if the location of the startup is in Mumbai and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
CONSUMER_INTERNET	Dummy variable that takes a value 1 if the startup belongs to a consumer internet domain and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
HEALTHTECH	Dummy variable that takes a value 1 if the startup belongs to healthtech and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
FINTECH	Dummy variable that takes a value 1 if the startup belongs to fintech and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
EDTECH	Dummy variable that takes a value 1 if the startup belongs to edtech and 0 otherwise. We obtained this data from Crunchbase, Traxn, and Techinasia
AGE	Age of the startup measured in years at the end of the sample period [to] July 2018. We obtained these data from Crunchbase, Traxn, and Techinasia
GENDER	Dummy variable that takes a value of 1 if one of the founders is male and 0 otherwise. We obtained this information from LinkedIn.