Social Is the New Financial: How Startup Social Media Activity Influences Funding Outcomes

February 7th, 2017

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Abstract

Early stage firms increasingly use social media to communicate with their target stakeholders, such as customers and investors. In this study, we investigate whether the use of social media is associated with increased success in raising venture capital financing. We argue that social media can improve startup funding success through two channels: 1) enabling investor discovery of potential investment opportunities through reduction of search costs and 2) providing additional information to investors for a better evaluation of the quality of the ventures. Using social media activities on Twitter and venture financing data from CrunchBase, we find that an active social media presence and strong Twitter influence (followers, mentions, impressions, and sentiment) increase the likelihood a startup will close the round, the amount raised, and the breadth of the investor pool. In addition, we find that startup social media activity is associated with more investment from investors with less information channels (e.g., angels) and making less industry specialized investments in particular, consistent with the hypothesis that social media improves an investor's ability to discover potential investments. Also, the effect size of social media is stronger for startups where quality information is less available, such as firms outside geographic venture capital clusters or where later investors do not have network relationships with early investors, consistent with social media acting as an additional information channel to inform startup quality evaluation.

Keywords: Social Media, Startups, Venture Capital, Search Cost

Introduction

With 72% of U.S. Internet users on Facebook and 23% on Twitter, social media has become an important conduit of information for individuals, firms, and markets. Social media provides an alternative channel for marketing communication, enabling firms to build their brands and interact with customers. The effectiveness of social media for marketing goods and services has been particularly well-studied in the context of established firms and product markets (Aral, Dellarocas, & Godes, 2013; Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). However, few studies have looked at the use of social media by emerging firms or the role of social media in the capital markets. In this project, we explore the intersection of these two areas to examine whether social media activities improve a startup's ability to raise capital from venture capitalists and angel investors, arguably one of the most important factors in the success of early stage firms.

The market for early stage private financing faces two distinct information challenges, both of which social media can address. First, startup firms seeking private equity or debt financing are not listed in centralized exchanges as are publicly traded firms, and investors need to engage in costly search to identify potential startups to finance. Startups that are "off the radar" due to their location or lack of existing relationships between the management team and potential investors are less likely to receive funding without alternative means of communication. Second, startups cannot provide much of the traditional information that investors use to evaluate firm quality, such as assets and cash flows histories, making it difficult for investors to evaluate their quality (Aldrich & Fiol, 1994). This problem is exacerbated by a principal-agent conflict where entrepreneurs have an incentive to exaggerate growth and earnings to attract investors and increase their equity valuation (Dessein, 2005). These information challenges can partially be attenuated by geographic agglomeration of investors and startups (Saxenian, 1991) that allows for more contact between investors and startups, and information networks among investors themselves (Hochberg, Ljungqvist, & Lu, 2007). Here social media provides an additional source of information that does not rely on geography or existing social networks among investors.

Social media acts as a medium for information exchange and offers solutions to both the costly search and information scarcity problems that market participants face. Startup firms can broadcast information about themselves over social media and thus raise awareness of their existence among potential investors, helping investors discover more early stage ventures and expand their consideration set of potential investment opportunities. In addition, startups' social media activities provide an additional channel of information for investors to use when evaluating investment opportunities. For example, popularity on social media could demonstrate a startup's ability to attract specific customer groups, build its brand name, and integrate feedback from consumers. Such positive social media information shows firm quality to investors and raises their expected return on the investment, and thus increases the startup's chances of getting funding successfully. Anecdotally, venture capitalists are increasingly conducting "due diligence" on social media platforms and reacting favorably to startups with effective social media performance. For example, Vandaele Capital LLC decided to fund Boxtera, a startup that delivers health-food packages to subscribers, because of their effective use of Twitter to reach their target audience.[1]

Regulators are also taking note of social media's growing role as a conduit for investment information. Historically, startups were restricted in their ability to make public offers or solicitations to sell securities, including on social media platforms. However, the substitution of social media for traditional information sources, such as press releases, has introduced ambiguity into the definition of appropriate communications to potential investors. Along with the implementation of various other provisions of the J.O.B.S. Act,[2] the U.S. Securities and Exchange Commission (SEC) issued a new policy in June 2015 allowing startups to tweet to potential investors about the opportunity to invest in them, something they were previously prohibited from doing on most public platforms. As this communications channel gains

[1] Wall Street Journal. "If You Look Good on Twitter, VCs May Take Notice". September 30, 2013. http://www.wsj.com/articles/SB10001424127887324659404578499702279196058

[2] Another provision of the Jumpstart Our Business Startups (JOBS) Act is the legalization of equity crowdfunding, the online offering of private equity securities to investors. While various forms of crowdfunding are likely to occupy a growing persistent component of the market for early stage equity financing, traditional venture capital and angel financing are expected to continue to dominate early stage private equity financing market for the foreseeable future. Nevertheless, our research on the implication of social media for venture capital and angel financing should also have implications for the future of social media in equity crowdfunding as well.

further legitimacy, it is becoming more important that we understand the policy implications for early stage venture financing markets and entrepreneurial performance.

Few existing studies have looked at the use of social media by emerging firms or the role of social media in the capital markets. Rather, existing studies on social media predominantly focus on marketing outcomes and on established firms. Studies have shown that social media promotes word-of-mouth information diffusion (Aral et al., 2013; Chevalier & Mayzlin, 2006; Dellarocas, Zhang, & Awad, 2007; Forman, Ghose, & Wiesenfeld, 2008; Zhu & Zhang, 2010) and serves as a platform for greater consumer engagement with a product or brand (Chen, De, & Hu, 2015; Ghose & Han, 2011; Goes, Lin, & Au Yeung, 2014; Li & Wu, 2014; Miller & Tucker, 2013). Recent studies further link social media activity and firm performance through mechanisms of marketing effectiveness (Chung, Animesh, Han, & Pinsonneault, 2014; Goh, Heng, & Lin, 2013; Luo, Zhang, & Duan, 2013) and value extraction from social media analytics (Hitt, Jin and Wu, 2015). However, there exist few studies directly examining the use of social media by and its effect on early stage firms, with the notable exception of related work by Aggarwal et al. (2012), who examine social media mentions of a firm (particularly on blogs) and venture financing; they find that negative electronic word-of-mouth has greater impact than positive word-of-mouth, and that the effect on financing decreases as a firm progresses to later stages of financing. In this study, we examine the direct use of social media by startup firms for corporate promotion on the likelihood of funding, focusing specifically on the role of social media in changing the costs or benefits of physical proximity.

This study bridges the information systems literature and entrepreneurial finance literature, providing empirical evidence for the effect of startup firms' social media activities on their funding outcomes. We construct a unique data set that combines financing rounds data for high-technology startups, as reported in CrunchBase, with historical data on Twitter activity by the same startups, from Topsy.com. We empirically investigate distinct hypotheses from two mechanisms through which social media facilitates entrepreneurial financing, i.e., how social media helps investors discover potential investment opportunities though search cost reduction, and how social media activity provides an additional channel of information for investors to assess startup quality.

We find that social media activity on Twitter improves a startup's chance of closing a financing round, raises the total amount of funding they receive in the round, and increases the number of investors participating in the round, after controlling for various firm-level characteristics. In addition, we find evidence supporting both of the mechanisms through which social media can influence startup funding.

First, we find evidence that startup social media activity reduces search costs in the market for entrepreneurial finance. Startups active on social media are likely to attract a larger portion of angel investors in early funding rounds; since angel investors are usually not full-time investors and have less alternative channels for information about possible investment opportunities as compared to VCs, social media plays a larger role in their discovery of potential startups to finance. Startups active on social media attract a larger portion of investors with diverse investment portfolios rather than concentrated investments in specific industries. For such investors, social media provides a low-cost channel to improve their awareness of startup activities across a range of industries. This is in contrast to investors who make repeated investments in the same industries. They generally build up personal connections and other sources of information to learn about new investment opportunities, making social media's role as an information-broadcasting channel less significant.

In addition, we find that startups located outside the primary clusters of VC activity in the U.S. (Boston, New York, San Francisco) engaged in effective social media activities experience a greater increase in their financing round size. Therefore, increased funding from social media activity to startups located in regions where it is harder for investors to inspect the startups in person, shows that positive information on social media can reduce uncertainty in startup quality and improve investors' valuation for the startups.

Second, we find evidence that startups' social media activities give investors information to better evaluate potential investment opportunities. When information about the quality of the startup is low, such as when investors do not have a prior co-investor participating in the current round and serving as an information source, social media plays a more important role in the evaluation of startup quality. We also find that startups active on social media are more likely to receive funding from experienced investors, especially when they do not have trusted sources of quality information through investor syndicate networks. Since experienced investors accumulated expertise analyzing startup quality from prior investments, they should be more effective in utilizing social media for assessment.

This study has several practitioner implications regarding social media's role as an alternative channel of information for startups and their investors. Specifically, entrepreneurs can take advantage of the new SEC regulations and leverage social media campaigns to seek investors. In addition to broadcasting their presence to potential investors, entrepreneurs can focus their social media strategy on portraying a positive brand image, demonstrating the ability to engage target customer segments, and sourcing informative customer feedback. From the investors' perspective, social media presents an alternative channel for discovering potential investment opportunities, particularly if they do not have existing connections or channels of information in certain industries. Investors can observe the social media activities of startups they are considering for investment, and use this information to assist in their investment decision.

Theoretical Background and Hypotheses

Private equity investments by venture capital firms and angel investors continue to be a dominant source of financing for early stage, high-growth, high-risk, technology businesses. In 2014, annual venture capital inflows topped $48 billion for these "startups", representing the highest levels in over a decade.[3] The two primary types of investors in this space are venture capital firms, which are professional asset management firms that invest using funds put up by institutional or large private investors, and angel

[3] PricewaterhouseCoopers LLP and National Venture Capital Association. January 16, 2015. http://nvca.org/pressreleases/annual-venture-capital-investment-tops-48-billion-2014-reaching-highest-level-decade-according-moneytree-report/

investors, who are high-net-worth individuals[4] investing their own funds.[5] These financial intermediaries specialize in the evaluation, investment execution, and post-investment monitoring of startups.

Venture capital firms and angel investors face two unique information challenges in discovering and evaluating investment opportunities. First, the lack of a centralized market for early stage private equity means that entrepreneurs and investors lack information about the existence of parties on the other side of the market, and thus they must undergo a costly search process (Inderst & Müller, 2004) in order to identify a possible choice set before they can even begin the process of information collection and evaluation (due diligence). In other words, possible investors may not even be aware of a particular venture and ventures may have limited knowledge of available funding opportunities. These search costs can be prohibitive, preventing legitimate high-quality ventures from obtaining funding on acceptable terms.

Second, startups lack many of the traditional physical assets and steady cash flow histories used to evaluate more established businesses (Aldrich & Fiol, 1994), so investors have less information and face substantial uncertainty when evaluating a new venture (Kaplan & Strömberg, 2004; Shane & Cable, 2002). The information problem facing investors is further exacerbated by an asymmetric information problem between entrepreneurs and investors (Dessein, 2005), that entrepreneurs have an incentive to over-represent the quality of their firm to investors in the hope of improving their chance at receiving an investment at a higher valuation. Thus, hard information for the evaluation of new ventures is rare and the marginal value of additional information is likely to be high (Amit, Glosten, & Muller, 1990; Gompers, 1995).

Social media can alleviate both of the above information problems by broadcasting information about the existence startup seeking financing to potential investors and by offering another channel of information for investors to evaluate startup quality through their social media activities.

Social Media and Organizations

[4] In the United States, angel investors must be accredited by the SEC, meaning they must have a net worth of at least $1 million (not including the value of their primary residence) or have an income over $200k each year for the last two years.
[5] New forms of entrepreneurial finance, such as peer-to-peer lending and crowdfunding, have developed in the last few years, but they continue to be a niche segment of the capital market for early stage private equity in both scale and influence.

While the literature on social media use has focused on established firms, the same insights apply to social media communications by early stage emerging firms.

Perhaps the most studied aspect of social media is its role as a new marketing channel to customers. A substantial literature has linked feedback from consumers, such as product reviews, to product sales and changes in marketing strategy (Dellarocas et al., 2007; Forman et al., 2008; Hong, Chen, & Hitt, 2014; Li & Hitt, 2008; Zhu & Zhang, 2010). In addition, social media contributes to long-run marketing performance, by providing an alternative channel for organizations to build brands and engage consumers (Ghose & Han, 2011; Goh et al., 2013; Lee, Hosanagar, & Nair, 2014; Rishika, Kumar, Janakiraman, & Bezawada, 2013; Shriver, Nair, & Hofstetter, 2013). Finally, social media serve as a platform for new marketing strategies that encourage information diffusion and social influence through network ties (Angst, Agarwal, Sambamurthy, & Kelley, 2010; Aral & Walker, 2011; Bapna & Umyarov, 2015). In addition to documenting the direct performance of social media on marketing outcomes, a new stream of research links these benefits translate to improvements in overall firm performance (Chung et al., 2014; Hitt, Jin, & Wu, 2015; Luo et al., 2013).

An emerging stream of work studies the impact of social media on entrepreneurs, with a focus on online capital markets, such as crowdfunding or peer-to-peer lending platforms (Agrawal, Catalini, & Goldfarb, 2011; Lin, Prabhala, & Viswanathan, 2013). Eesley and Wu (2015) study the motivation for social network connections between entrepreneurs and their mentors and how these connections affect firm performance. Greenwood and Gopal (2015) examine how media coverage of a technology segment influences the number of new startups founded in that segment. Aggarwal, Gopal, Gupta, and Singh (2012) identify a link between blog mentions and sentiment about startups and subsequent financing outcomes. (Agrawal et al., 2011; Lin et al., 2013) study the peer-to-peer lending market and find that stronger social network relationships are associated with a higher likelihood of a loan being funded, a lower risk of default, and lower interest rates.

Taken broadly, existing studies suggest that the use of social media can influence overall firm performance, including the success of early stage firms and their ability to obtain financing. A new emerging trend of literature also finds evidence of firms' active presence on social media leading to increased market value, suggesting that firms' activities on social media can also influence investors' evaluation of firms' equity value (Goh et al., 2013; Luo et al., 2013). While these studies mostly use data from established companies, we expect to see similar logic at work for startup firms. Based on the logic of the aforementioned studies and the two mechanisms we will outline immediately after this, we hypothesize that startups more active on social media are more likely to succeed in their funding process:

Hypothesis 1: *A startup active on social media is more likely to receive* ***larger amounts*** *of funding from investors.*

Hypothesis 2: *A startups active on social media is more likely to receive funding from* ***a larger number*** *of investors.*

The next two sections outline the two specific mechanisms, namely search cost reduction and startup quality information channel, that together drive Hypothesis 1 and Hypothesis 2. We will also describe distinct hypotheses from these two mechanisms that enable us to disentangle them.

Search Costs and the Discovery of Investment Opportunities

Unlike publicly traded companies, early stage startup firms do not have a centralized market where investors have easy access to all potential investment opportunities. In fact, private equity investors and entrepreneurs engage in a costly search process to find one another (Inderst & Müller, 2004). Furthermore, there exist few brokers connecting startups with investors, a role played by investment bankers in the case of large mature firms. Search costs constitute a significant barrier limiting investor awareness of the full set of investable startups.

A long stream of information systems literature examines the role of IT in reducing search costs. Digital communications technologies can substitute for geographic proximity, enabling firms to locate "closer" to customers or their target markets without incurring significant costs of coordination or uncertainty (Bakos & Brynjolfsson, 1993; Clemons & Row, 1992; Gurbaxani & Whang, 1991; Malone, Yates, & Benjamin, 1987). Like prior advances in information technology, social media presents a similar opportunity for lowering the cost of communication, which is particularly salient for early stage firms that may not have developed more traditional marketing capabilities that require greater upfront capital investment.

In this study, we focus on the social media site Twitter, whose open platform enables firms to broadcast information to a targeted audience (Chen et al., 2015). Twitter's platform design enables users to follow anyone they wish, making it an effective channel to distribute information to a large group of already interested users (Fischer & Reuber, 2011). Just as established firms can use Twitter to reach to customers, startup firms can also use it to broadcast about themselves and reach out to a larger pool of both customers and investors. Since investors have easy access to information on Twitter, this low cost information channel can broaden their pool of potential investment opportunities.

While social media information is equally available to all types of investors, it may be especially valuable to investors lacking the formal information channels through which they source their set of possible investment deals. Angel investors, who are not usually full-time investors, usually do not dedicate a substantial amount of time to sourcing possible investments, and they do not have the support staff or access to institutional information available to venture capital firms (Lin, Sias, & Wei, 2015). However, angel investors should have comparable access to information arising from social media. Since angel investors likely face higher search costs in the absence of social media, we expect to see social media playing a larger role in their discovery of new investment opportunities.

Hypothesis 3: *A startup firm active on social media is more likely to receive funding from more angel investors.*

Many investors concentrate their investments in a limited number of industries to better leverage specialized expertise and business relationships that would help identify new opportunities (Sorenson &

Stuart, 2001). Investors making investments in a few specific industries can rely less on social media to discover new investment opportunities. On the other hand, for investors interested in making diverse investments across different business categories, it would be costly to sustain a significant base of contacts in each line of business to stay informed about potential startups to finance. Therefore, we expect social media to play a larger role in the discovery of startups to invest in for investors with diverse portfolios.

Hypothesis 4: *A startup firm's social media activities have less effect on investors making concentrated investments in certain industries.*

Hypothesis 5: *A startup firms active on social media is more likely to receive funding from more investors with diverse investment interests.*

Social media will player a greater role in reducing search cost when other information channels, such as in-person interaction, are limited. Geographic distance makes it more difficult for investors to obtain quality information on startups, since information circulates more freely between geographically proximate people and firms (Rosenthal & Strange, 2004). This pattern also holds in the venture capital industry: VC investments are geographically concentrated (Sorenson & Stuart, 2001), and 49% of all VC investments are made to startups located in the Boston, New York and San Francisco metropolitan areas (Chen, Gompers, Kovner, & Lerner, 2010). Startups located outside these VC clusters usually lack the face-to-face interaction channels to build reputation and trust as startups located closer to investors do, and it is also costly for investors to actually visit and inspect the startups located further away (Ivković & Weisbenner, 2005; Lerner, 1995; Massa & Simonov, 2006). Therefore, we expect to see social media playing a more important role, where investors have fewer channels of information to look up for startups outside VC clusters.

Hypothesis 6: *A startup located further away from a VC cluster regions will experience a stronger effect on their financing outcomes from social media activities.*

Information Channel for Investor Evaluation

Beyond the search costs related to discovering investable startups, investors also have limited information on which to evaluate their investments in new ventures, a problem exacerbated by an asymmetric information between investors and entrepreneurs where entrepreneurs have an incentive to over-represent their quality. Investors engage in a complex information acquisition process (due diligence) to screen and evaluate investment opportunities; the ability to evaluate deals is a key performance differentiator among early stage investors (Gompers, 1995; Van Nieuwerburgh & Veldkamp, 2009).

Prior studies show that activities on social media can reveal information on firm quality to investors in online financial markets. Social media presence increases the success of crowdfunding activities (Agrawal et al., 2011). Similarly, more social media contacts ("friends") on a peer-to-peer lending platform increases the chance of reaching a funding target (Lin et al., 2013). In addition, early stage firms usually do not have a fully functional product or service ready for sale yet, so social media success could reveal the potential market size and customer reception for the product or service, thus foretelling a startup's chance of success. Anecdotal evidence also suggests that investors are increasingly evaluating metrics of social media presence, such as the number of followers on Twitter or other metrics of social media reach—as well as the sentiment of social media content (e.g. reviews, feedback) about a firm—when they make investment decisions.[6] An effective social media presence can serve as a signal of startup quality in an investor's evaluation process.

The role of social media as an additional startup quality information channel depends on the investor's ability to process information. Experienced investors accumulate expertise and knowledge that enable them to better process information and evaluate the quality of startup firms (Sørensen, 2007). These investors should be more effective in analyzing the information from social media to evaluate startups and

[6] Wall Street Journal. "If You Look Good on Twitter, VCs May Take Notice". September 30, 2013. http://www.wsj.com/articles/SB10001424127887324659404578499702279196058,

guide their investment decisions. Therefore, we expect that startups active on social media are more likely to obtain investment from experienced investors.

Hypothesis 7: *A startup active on social media is more likely to receive funding from experienced investors.*

On the other hand, the role of social media in providing quality information on startups will be moderated by the existence of other information channels for the investors. One such channel is the network of co-investors from past syndicated rounds. Venture capital firms and angel investors who jointly make VC funding in a given startup are referred to as “syndicate partners”. These syndicate partners have a substantial amount of interaction through the process of executing the round and then *ex post* through advising and monitoring the startup. Thus, prior syndicates reveal close collaborative relationship between investors where information is shared (Hochberg et al., 2007). If investors have previous syndicate partners who invested in a startup in an earlier round, they can acquire information on the startup quality from these partners, making alternative quality information sources like social media less important.

Hypothesis 8: *A startup’s social media activities have less influence on investor with previous syndicate partners already invested in the startup.*

Data

Sample Construction

The main dataset consists of investment rounds into new technology-based ventures in 2007–2015 obtained from CrunchBase, combined with data on startup social media activities on Twitter from Twitter API and Topsy.com.[7] Crunchbase records information on startups, people affiliated with the startups and investors. It focuses specifically on the information technology sector and has been considered to be representative of venture activity in their target markets (Block & Sandner, 2009; Wu, 2015). The

[7] Crunchbase is operated by TechCrunch, an AOL Inc. subsidiary delivering news on the information technology sector. Topsy.com is a certified Twitter partner, and maintains an archive of Twitter activity dating back to time Twitter was established (2006).

Crunchbase data archive is obtained from a combination of user input and regulatory filings which are then reviewed for accuracy and compiled by TechCrunch staff. For each startup, there is data on the characteristics of each funding round to date (date, amount raised, type of funding, investor), characteristics of the venture itself (founding date, employee count, type of business), and characteristics of the founders (prior venture experience and prior management experience).

We utilize Twitter as the source of social media data since it is the social media platform most extensively used by startups and investors, and broadly used by the business community; 60% of startups in our sample use Twitter while only 47% use Facebook and 36% used LinkedIn. The Twitter adoption rate for startups across different business categories are shown in Figure 3.1. We observe substantive Twitter usage by startups in different lines of business, with higher Twitter adoption rate in the news, media and information related industries, and lower adoption by transportation and manufacturing related businesses, as one would assume.

Some firms were excluded because the screenname utilized common English words (e.g., "path", "square", "tune") which contaminate the data construction process on Twitter and Topsy.com, which rely on a text search of the firms' screenname.

We focus specifically on the 2nd round of VC financing for three reasons. First, we do not want to use the 1st round of financing because not all startups are raising money, and we would not be able to empirically distinguish between those not raising money ("bootstrapping") and those who are. Once a startup closes a 1st round of funding, it reveals that the firm is not bootstrapping, and consistent with the path of most technology startups backed by equity financing, they likely to need additional rounds of funding to sustain the firm. Second, we want to focus on earlier rounds of financing where public and private information available to investors is low and our theorized roles for social media still matters in reducing search costs and serving as a quality signal. In the later funding rounds, the theorized role of social media as an information channel would be harder to detect since there the startup firm has a track record already. Combining these first two points, the 2nd round is obviously the earliest round that isn't the 1st round. Third, using the 2nd round allows us to use the 1st round as a control for firm size and quality.

Our data is primarily collected prior to the recent SEC regulation change in June 2015. In our observation window, startup firms have restrictions on the content they post on social media, specifically limiting the announcement of investment information to the public. We expect to see that after the regulation change, startup firms will more actively use social media to reach out to investors, and but exact empirical effect of social media on financing outcomes remains an open empirical question for future research.

Social Media Variables

We identify the Twitter page and screenname for each firm's corporate account (if it exists), and then use the Twitter API and Topsy.com API to gather information on Twitter activity, including:

-- **Number of tweets posted**: the number of distinct Tweets for each screenname that contain a link;[8]

-- **Mentions:** the number of distinct social media posts (tweets or links) that mention a startup's Twitter screenname in each month;

-- **Impressions:** the number of potential views of a firm's Tweets in each month;[9]

-- **Sentiment:** a normalized score from 0 (most negative) to 100 (most positive) based on the sentiment of all tweets mentioning a firm's screenname in each month;[10]

-- **Number of followers:** a count of the number of Twitter followers for each screenname.[11]

[8] Drawn from the Topsy.com archive, we utilize this proxy in lieu of the raw number of Tweets due to data limitations.
[9] The Impressions variable is provided by the Topsy.com API, calculated by multiplying the number of tweets mentioning the startup's by the number of followers during each month of our sample period.
[10] Sentiment was provided by the Topsy.com API.
[11] The number of followers was constructed for our dataset by taking a snapshot at a single point in time, namely June 12th, 2015 at 18:00.

We include 3 measures of Twitter activity: 1) whether the firm created its Twitter account prior to receiving the 2nd round funding (***Started Using Twitter***), 2) the total number of Tweets posted in the 12-month-window prior to receiving the 2nd round funding (***Number of Tweets***), 3) the first principal component of the number of mentions, impressions, followers, and sentiment in tweets mentioning the Twitter account of the startup (***Twitter Influence***).

Dependent Variables

We focus on funding outcomes as the dependent variable (closing a 2nd round of funding, the number of investors participating in the 2nd round, and the size of the 2nd round funding) rather than other kinds of startup or VC performance measures (e.g. startups' successful exit; investors' returns to investment) because we are currently concerned with the link between social media and financial markets for early stage capital, although looking at other performance measures would be an excellent avenue for future research. The size of a funding round is a good general measure of fundraising outcomes, and since larger amounts raised are correlated with larger valuation, it also provides some insight on the investor's expectation of the startup's profitability and growth.

Control Variables

We include controls for startup characteristics (age, employee count, and number of different lines of business, other funding received prior to 1st round VC funding), founder experience (prior startup experience, prior executive-level management experience), industry (industry indicators), and year received the 2nd round funding (year indicators). The time and industry controls address market-wide conditions that could potentially affect funding. Overall, these variables control for variation in startup quality and are consistent with the prior literature on entrepreneurial financing (Hsu 2007).

To isolate the effects of Twitter from general online presence or other social media, we include controls for web site traffic rank (Alexa rank of a firm's homepage URL), search popularity (Google Trends data for a firm name as a search term), and an indicator for the firm's presence on Facebook. These variables also control for other marketing activity and brand awareness in addition to directly measuring online presence.

To control for communication from between prior investors in the startup to other investor through their personal contacts, we include a measure of investors' network connections through their syndicate partners. We use the PageRank measure to capture how well-connected the investors are and their ability to spread word about the startup to other investors; the PageRank measure captures the relative importance of nodes by factoring in how many connections they have and how important these connections are (Brin & Page, 2012).

By including an extensive number of startup firm characteristics, including the size of the 1st round of financing, we control for many sources of unobserved firm quality that could potentially confound our estimates of social media's effect on funding success. Furthermore, since many of these variables are lagging indicators (prior year firm characteristics) or measures of changes (e.g. a firm adopting Twitter), we are less vulnerable to simultaneity between investment and social media use.

Summary Statistics

We report the summary statistics and correlation between main variables of interest in Table 1 and Table 2. Our data includes 2,880 startup firms, for 2nd round funding events across years 2007-2015. The data is structured in a cross-sectional, with each startup firm appearing once. Social media measures are matched to the specific time-window before the 2nd round funding. Most of the other controls—such as firm age, website traffic, Google Trends measures, and founder controls—are matched to the specific timing of the round as well. However, our measures of number of employees and the number of followers on Twitter, with are fixed based upon our time of data collection, and the year indicators should address the natural time trend in these variables.

Empirical Methodology

To test our main empirical hypotheses, we estimate a basic regression model structured at the investment level. We further confirm the robustness of our findings against possible endogeneity stemming from the omitted variable of startup quality with an instrumental variables analysis. We also present a panel regression model in our appendix.

Main Analysis

After log-transforming the round size measures, we estimate the following ordinary least squares model (with robust standard errors):

$$\log(2ndRoundFunding) = \beta_0 \log(1stRoundFunding) + \beta_1 Interval$$

$$+\boldsymbol{\beta_2 Started\ Using\ Twitter} + \boldsymbol{\beta_3 NumberofTweets} + \boldsymbol{\beta_4 Twitter\ Influence}$$

$$+\beta_5 WebsiteTrafficRank + \beta_6 GoogleTrend + \beta_7 OtherPlatform$$

$$+startup\_controls + founder\_controls + business\_category + year + \varepsilon$$

The model relates the amount raised in the 2nd round of financing to the amount raised in the 1st round of financing, the time elapsed between rounds and the Twitter activity measures.

Instrumental Variables Analysis

One main endogeneity concern with the empirical analysis is that both social media activities and entrepreneurial financing could be influenced by the latent startup quality. In the main OLS analysis, we control for some of this through the website traffic and Google Trend controls, measuring the general public's interest in the startup firms, accessing the startup homepages for product and service offerings or searching for the relevant information. In addition, we seek to reduce the effect of this type of endogeneity through the use of instrumental variables. Our identification strategy focuses specifically on the model which utilizes funding outcomes as the dependent variable, since that model is most likely to be affected by unobserved startup quality that might simultaneously influence social media influence. Using the same instruments in the other models yields similar outcomes to the OLS results for these as well.

We use the following three sets of instrumental variables. First, we use social media activities of other startups located in the same region. For each region and year combination, we look at the Twitter presence, number of tweets posted and Twitter influence measures respectively for other startups located in the same region. Twitter usage for firms located in the same region is likely to be influenced by similar factors, like the number of Twitter users in the region and users' propensity to interact with startups online but other firms' social media activities should not directly influence the startup's own funding outcomes. Second, we use social media activities of other startups that their investors previously invested in. If investors have different preferences of social media usage, this will lead to a correlation of social media use among firms; however, since investment amounts depend on firms specific factors they are unlikely to be correlated (especially since multiple investors tend to participate in the same investment round). Finally, we use a geographic measure of the awareness and use of Twitter using Google trends data on the search term "twitter" from 2007-2015 in each state. If startups in this region are more active on Twitter, we expect this to be reflected in the Google Trends, as consumers query for Twitter related information. This instrument should be correlated with the social media metrics of the startups, but not be directly linked to startup quality or funding outcomes.

Results from 2nd stage of 2SLS regression, using these three sets of IVs to instrument for startups' starting the Twitter pages, number of tweets posted on Twitter and Twitter influence measures and using 2nd round funding as the dependent variable, are reported in accompany with each set of OLS results. We do not find evidence of weak instrument problems based on the usual tests for first stage predictive power ($F(65, 2694) = 38.11$, $p= 0.0001$). Since the instruments help tease out the effect due to better quality startups also more likely to be present on social media, we are able to better estimate the impact of social media on startup funding. Results are largely consistent with what we observed before: presence on Twitter improves startups' amount of funding collected. This effect is mainly driven by Twitter influence rather than Twitter activity. The economic size of the effects are comparable with the OLS estimates, for example, columns (3) in Table 4 indicates that a one standard deviation increase in the Twitter Influence measure leading to about $3.1 M increase in next period funding. The fact that our results are not weaker when using 2SLS estimates indicate that it is unlikely for our results to be entirely driven by endogeneity.

Results

Social Media Activities and General Funding Outcomes

To test our initial hypotheses that social media use is related to funding outcomes, we estimate Equation (1) for the full set of startups for which we have complete data using ordinary least squares (OLS). We first take a look at the overall influence of social media activities on startup funding outcomes, using data on startups' total amount of funding collected and the number of investors that they collect funding from in the 2nd VC funding round. In Table 3, we report the results relating the log value of total funding collected to the social media metrics and other control variables. The control variables all have signs in the right direction: startups who collected larger amount of funding in the 1st round, having more visits to their webpages (lower traffic rank) and attention from consumers (higher search volume as reported in Google Trend for query of startups company names) are also likely to collect more funding in the 2nd round; shorter interval between the two rounds are related to larger amount of 2nd round funding, as do startups with founders that worked on more startup projects previously and with more executive management experience, but the effect sizes are smaller in these cases[12].

Regarding the social media activity measures, we show that just being present on Twitter, without active posting or engaging with users, does not lead to startups' receiving larger amounts of funding (column 2, Table 3). This suggests that simply starting a Twitter page does not automatically gets the startup firm more funding, which is consistent with prior studies that found that it is active use of social media that generate desired outcomes for the firms (Miller & Tucker, 2013). We also observe that the number of tweets startups post on Twitter does not significantly influence its funding outcomes either. There appears

[12] We control for startups presence on Facebook here, but do not control for LinkedIn presence, mostly because it is not commonly used as a channel for information distribution for startups, but mostly used by employees to list their places of employment and for recruitment purposes.

to be a mild quadratic relationship between the number of posts and funding outcome (column 4), suggesting that posting more tweets initially benefit the startups, but posting too much content can actually hurt the firm (with the peak at about 290 tweets per year and when tweeting more than 580 tweets per year, it could actually hurt the startup). The shape of the quadratic function is very flat though, indicating that in general the effect size of number of tweets on funding outcomes is quite small. Startups can't necessarily benefit from social media simply by tweeting a lot. This is consistent with prior literature that mentioned posting too much information could actually have a negative effect, most likely due to the cost of managing tweets and lack of channel to really absorb the information collected from social media (Fischer & Reuber, 2011). These results indicate that startups need to actively manage their content on social media, to better engage other users, in order to see the benefits from social media. In fact, we see strong positive effect of all the metrics relating to startups' influence on Twitter. Specifically, getting mentioned more in other people's tweets, have more impressions of tweets, with more positive sentiments in others' tweets mentioning the startup firm and a larger follower-base can all improve startups' funding outcomes. Since these measures are correlated with one another and show consistent results, we take their 1st principal component (Twitter Influence), to capture the overall impact (column 1, Table 4). We find that a one standard deviation increase in the Twitter Influence measure leading to extra \$1.5 million in 2nd round funding. This is equivalent with any of the following: 1) increase of number of mentions by 4.6%; 2) increase of number of impressions by 12.0%; 3) Increase the number of followers by 209,815; 4) Increase of average sentiment score in people's tweets mentions of the startup firm by 0.02 (with all negative sentiment as -1 and all positive sentiment as 1). Consistent results are obtained when we use the subsample of startups who have started Twitter pages prior to receiving their 2nd round funding (column 2). Columns (3) and (4) report two stage least squares regression results. In column (5), we run the same regression using Heckman selection model on a larger sample of all startup firms that received first round funding, and showing that we get consistent results considering that we only observe 2nd round funding information for startups that receive 2nd round funding. In column (6), we use the same sample as (5), and use the dummy variable of whether the firm receives 2nd round funding as the dependent variable, to run a Logistic regression, showing that both being present on Twitter and having stronger influence on Twitter increases the likelihood for startups to receive 2nd round VC funding. These results support our first hypothesis that social media activities improve startups' funding outcomes.

Next, we look at whether startups' activities on Twitter allow them to draw in a larger pool of potential investors. In Table 5, we use the total number of investors in the 2nd VC funding round as the dependent variable, and found that startups with more influential social media profiles are likely to get more investors to make investments to them in the 2nd round VC funding (columns 1-2). Using alternative regression frameworks, such as the negative binomial model (columns 3-4) and 2SLS (columns 5-6) show consistent results. These results support our second hypothesis that social media activities help startup firms get funded by a larger pool of investors.

The above results consistently demonstrate that startup firms' social media activities influence their funding outcomes. Startups should be effective in their social media activities to build a positive brand image, draw in a larger followers group, get more users to retweet their messages and have people leave more positive feedbacks relating to their business. Startups that are more successful at generating influence on social media see higher chances of continuing to receive funding, from a larger pool of investors and getting larger amounts of funding overall.

Social Media Activities and Discovery of Investment Opportunities

We have demonstrated so far that startups' social media activities contribute to funding success. In the next step, we turn to investigate the mechanisms of social media's influence on startup funding, through the discovery and evaluation of investment opportunities respectively. Firstly, we take a look at how social media presence influences investors' search for potential startup firms. We hypothesized that for investors with fewer channels of information to learn about potential investment opportunities, social media's function as a platform for broadcasting information is more important. We test for this by examining the composition of investors participating in startups' 2nd round funding, looking at the number of angel investors,[13] while controlling for the total number of investors in the round.[14] In columns (1) and (2) of Table 6, we show that startups present on Twitter are more likely to have a larger portion of angel investors in the 2nd round[15], whereas Twitter Influence have less influence here. Since we are controlling for existing investors spreading word out about this startup by the PageRank measure of existing investors' VC syndicate connections, the result that more angel investors joining in the 2nd round for startups with Twitter accounts is most likely due to investors' discovery of new investment opportunities through social media. Consistent results are observed if we only look at the number of angel investors who newly joined in the 2nd round and did not participate in the first round funding, therefore making the discovery and information channel more salient (columns 3 and 4) and using 2SLS regressions (columns 5 and 6).

Investors' own experience from previous investments and particularly investments in certain industries also build up connections that investors can refer to in order to learn about new investment opportunities. Therefore, we expect to see social media as play a larger role in discovering startups for investors with more diverse investment portfolios. On the other hand, for investors making concentrated investments in certain industries and have consequently accumulated channels of information to learn about new investment opportunities, we expect to see social media playing a smaller role. To measure the diversity in investors' investment portfolios, we look at the investors' previous investments in other startups and the business categories they belong to. We define investors ranked in the upper 25th percentile of number of categories covered in previous investments as investors making diverse investments[16]. Investors with industry focuses as defined as those with total number of business categories covered in previous investments ranking in the lower 25th percentile.

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[13] Since detailed data on amount of funding in dollar amounts contributed by each investor is unavailable and generally rare, therefore, we only look at angel investors count and share.

[14] While angel investors generally invest in earlier stages of startups' development; it is not uncommon for angel investors to participate in the VC funding rounds as well.

[15] We are using the number of angel investors participating in the 2nd round funding here. Results are consistent if we use the number of all angel investors have not participated in previous rounds and only newly joined in the 2nd round; similar for the investors with diverse portfolios and investors with industry focuses. Also, we get consistent results if we put the percentage of angel investors in the 2nd round as the dependent variable.

[16] Similar results if we use the Herfindahl-Hirschman Index of previous investments across different categories to define diversity of investors' portfolio.

Columns (1)-(4) in Table 7 show that startups active on social media are more likely to get more investors interested in making diversified investments to participate in the 2nd round funding. In contrast, columns (5) -(8) show that startups active on social media generally have a lower ratio of investors making investments in specific industries. Together, these two piece of evidence suggest that for investors investing in a business category they are familiar with, having sufficient connections with other investors and entrepreneurs to hear about new investment opportunities, social media's role of broadcasting information about startups and potential investment opportunities is less salient. On the other hand, for investors interested in making investments across multiple business categories, who are less likely to be master in all the categories, social media can be an effective channel of learning about startups in different lines of business and expanding the potential pool of investment opportunities.

Next, we look at the funding outcomes for startups located outside VC clusters, i.e. outside the Boston, New York and San Francisco regions. These startups are located further away from investors and geographic distances can potentially exacerbate the search cost and difficulty in obtaining information on startups. In Table 8 we use the dummy variable (***Far from VC***) to indicate startup location outside VC clusters and include its interaction terms with the social media activity measures. Results show that while startups located outside the VC clusters in general receives less funding than startups located inside the VC cluster regions, they see additional gains in funding size from Twitter Influence, with one standard deviation increase in Twitter Influence metrics adding $1.5 million more funding, compared with startups located inside VC clusters (column 2). These findings suggest that for startups located further from VCs, where investors incur higher cost to obtain information, social media could present an additional information channel.

Overall, results support our hypotheses 3-6, showing that social media facilitates the entrepreneurial financing process, by providing information about startups, reducing the search cost and encouraging investors to explore a wider pool of startup firms, especially for investors with fewer channels of information, and for investors looking to make investments across different business categories but lack the industry connections to know about potential investment opportunities otherwise.

Social Media as Additional Information Channel for Startup

Once investors have identified the potential startup firms, the next step is for them to evaluate the investment opportunity and decide whether to actually fund each startup. We hypothesize that social media helps investors with this process, by providing more information about startup quality. For example, from startups' social media profiles, investors can learn about the startup's ability to build brand names through the online channel, reach out to target client groups, and also about consumers' feedback on the startups' products and services. Such additional information can help investors better evaluate the quality of the startup firms and make their investment decisions.

As supporting evidence for the role of social media in conveying information about startup quality, we look at startups' ability to reach out to the experienced investors. Hypothetically, if social media only works through the channel of discovering more investment opportunities, then startups should attract more average investors and more experienced investors in similar patterns, with their active social media presence. However, if the information on social media provide useful information on startup quality, then the experienced investors are more likely to effectively use the information in making their financing decisions. We examine this mechanism in Table 9, taking a look at how social media activities influence the number of experienced investors in the 2nd round funding, i.e. those who has made more than 100 investments up to date (which is the 80th percentile of investments made up to date for all investors[17]), while controlling for total number of investors in the round. Results are consistent with our hypothesis, showing that startups with more influence on Twitter get a higher portion of experienced investors (column 1), similarly if we look at the subsample of Twitter users only (column 2). These results suggest that startups more active on Twitter disproportionally attracts more experienced investors to invest in them, most likely

[17] Other thresholds to identify experienced investors show consistent results.

because these investors are more capable in analyzing the information on social media to discover startup quality and make investment decisions accordingly.

On the other hand, if the investors already have trusted channels of information to learn about the quality of the startups, we expect to see the role of social media as an information channel to be of less significance. Specifically, we look at whether there are investors from previous funding rounds who are partners with investors in the 2nd round in the same VC syndicates for other projects. If so, investors in the 2nd round can obtain credible information about this startup from these syndicate partner investors and rely less on information from social media to deduce the quality about the startups. Evidence supports this hypothesis: in columns (3) and (4), we control for the percentage of investors in the 2nd round with partners from previous VC syndicates already invested in the same startup firm (***VC Syndicate***), and include its interactions with the social media measures. We observe that when a larger portion of the investors have alternative channels of learning about startup quality from previous syndicate partners, the effect of social media in presenting quality signal for startups and attracting experienced investors to join in is less significant. These results support our hypotheses 7 and 8, showing that social media not only act as a channel of broadcasting information about startups and letting investors discover the startups, but also provides investors with another information channel to learn about startups' quality and helping with their evaluation process.

Conclusion

We find that startup firms active on social media have higher chances of getting funded, receive larger amounts of funding, and have a larger number of investors—all consistent with the idea that social media provides information that facilitates venture funding. These effects are attributed to social media influence rather than simply started using social media. We further find these effects are larger for investors that might lack channels for discovering investments (angels, diversified investors), and that funding outcomes are improved in conditions where there is likely to be significant information asymmetry (ventures located outside VC clusters, investors lacking social network ties to get information about a startup). Thus, the gains associated with social media appear to be attributable to both an awareness effect, where investors can learn about a larger number of potential investments, and an uncertainty reduction effect, where uncertainty about quality is reduced in settings where alternative quality signals are less effective. These results are robust to various econometric methods (controls, instrumental variables) for accounting for the problems related to unobserved variation in startup quality.

Our results highlight the importance for early stage ventures to establish a presence on social media, especially where social media success can provide an indicator of their ability to attract and retain customers. However, even firms that are not in consumer-facing industries can still benefit from expanding awareness among investors. Given that our data is primarily in a period when there were restrictions on social media activity that limited investment-related communications, recent legislative changes that now allow for greater information sharing on social media will likely increase the effect of social media on funding success. Our results also imply that while "cheap talk" in the form of Twitter posts does not have much influence on funding as would be expected, the ability to effectively engage readers in social media (influence) does matter, suggesting benefits of even modest improvements in information availability in settings where there is considerable information asymmetry. While the use of extensive startup and social controls contrasts within the data, and instrumental variables for addressing unobserved heterogeneity in startup quality does suggest the possibility that these effects are causal, in future work we hope to explore the specific communications more directly to gain a better understanding of how this information is communicated by looking at the specific content of social media interaction. Overall, we hope that this study and future related studies contribute to a better understanding of how the entrepreneurial financing market is changing due to social media and what startup firms should do to take advantage of the new opportunities that come with it.

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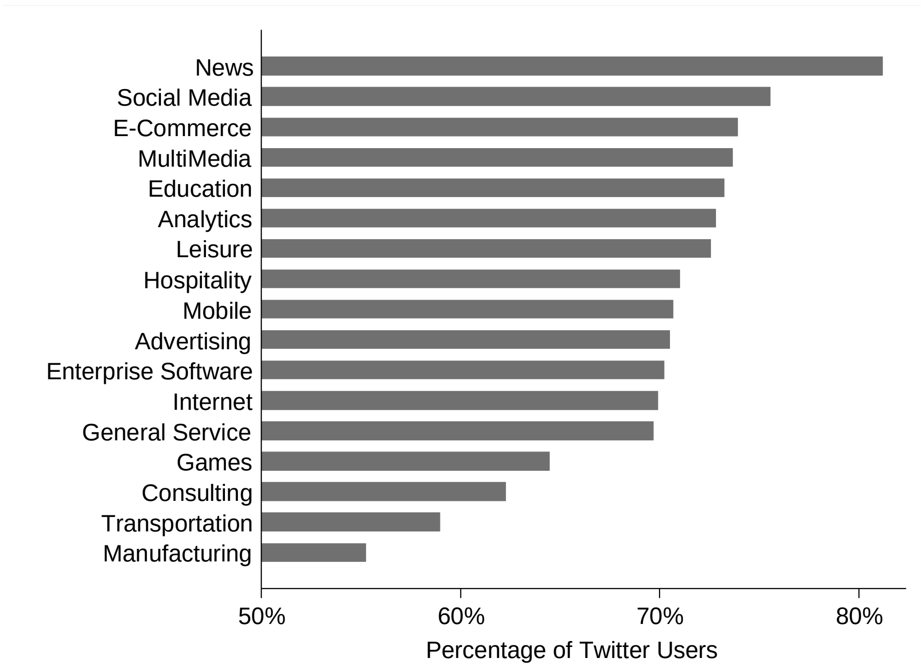
Figures & Tables

Figure 1. Twitter Adoption Rate across Startup Business Categories



Notes: 1. This graph shows the percentage of Twitter users for startups in different business categories; startups who has started a Twitter page by the time of our sample collection (June, 2015) are counted as Twitter users.

Table 1. Summary Statistics

Funding Round	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
2^{nd} round funding	2,880	15,100,000	21,600,000	50,000	542,000,000
1^{st} round funding	2,880	6,994,867	8,027,593	48,268	124,000,000
Months between 1^{st} and 2^{nd} rounds	2,880	18.94	10.65	0	95
Year received 2^{nd} round funding	2,880	2011.07	2.63	2007	2015
Number of Investors in 2^{nd} Round	2,880	3.491	2.422	1	29
Firm Controls					
Website Traffic Rank	2,880	2,550,414	1,034,335	444	3,267,739
Google Trends	2,880	6.76	13.30	0	78.5
Startup Age	2,880	3.60	2.04	0	10
Number of Business Categories	2,880	2.58	1.99	1	14
Employee Count	2,880	1,451.358	10,620.75	1	87673
Existing Investors' Page Rank	2,880	0	1	-1.18	3.305
Founder Controls					
Founders' Previous Projects	2,880	1.604	0.88	1	17
Founders' C-Level Experience	2,880	0.89	0.78	0	17
Twitter Measures					
Started Using Twitter	2,880	0.55	0.497	0	1
Number of Followers	2,880	13,763.51	97,573.78	0	2,439,962
Number of Tweets	2,880	265.15	747.30	0	12,914
Twitter Mentions	2,880	4,262.14	29,334.13	0	764,171
Sentiment	2,880	37.39	27.24	0	99
Impressions	2,880	160,162.4	746,651.4	0	9,397,203
Twitter Influence	2,880	0	1	-0.184	22.90

Table 2. Correlations between Main Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. 2nd round funding	1.00							
2. 1st round funding	0.34	1.00						
3. Months between 1st and 2nd rounds	-0.01	0.02	1.00					
4. Website Traffic Rank	0.01	0.04	0.06	1.00				
5. Google Trends	0.04	0.01	-0.08	-0.13	1.00			
6. Started Using Twitter	0.01	-0.03	-0.05	-0.09	0.13	1.00		
7. Number of Tweets	0.00	0.01	0.00	-0.08	0.11	0.32	1.00	
8. Twitter Influence	0.01	0.00	-0.03	-0.04	0.16	0.17	0.20	1.00

Table 3. Startup Social Media Activities and Funding

DV: **log(2nd round funding)** Label	(1) Base	(2) Started	(3) Tweets	(4) Tweets^2	(5) Mention	(6) Impressions	(7) Sentiment	(8) Followers	(9) All
log(1st round funding)	0.549***	0.549***	0.549***	0.549***	0.547***	0.547***	0.550***	0.549***	0.546***
	(0.0261)	(0.0261)	(0.0261)	(0.0261)	(0.0261)	(0.0259)	(0.0261)	(0.0261)	(0.0259)
Interval between Rounds	-0.00216	-0.00216	-0.00214	-0.00213	-0.00218	-0.00193	-0.00218	-0.00214	-0.00183
	(0.00163)	(0.00163)	(0.00163)	(0.00163)	(0.00163)	(0.00161)	(0.00163)	(0.00164)	(0.00161)
Website Traffic Rank	-0.00725	-0.00730	-0.00715	-0.00402	-0.00207	-0.00283	-0.00245	-0.00687	0.00265
	(0.0264)	(0.0264)	(0.0264)	(0.0156)	(0.0264)	(0.0261)	(0.0264)	(0.0264)	(0.0153)
Google Trends	0.00333***	0.00335***	0.00341***	0.00337***	0.00290***	0.00335***	0.00305***	0.00324***	0.00318***
	(0.00104)	(0.00104)	(0.00104)	(0.00104)	(0.00104)	(0.00104)	(0.00105)	(0.00104)	(0.00105)
Has Facebook Page	0.0865***	0.0901***	0.0911***	0.0882***	0.0799**	0.0723**	0.0847**	0.0897***	0.0699**
	(0.0334)	(0.0340)	(0.0341)	(0.0340)	(0.0342)	(0.0341)	(0.0341)	(0.0341)	(0.0342)
Existing Investors' Page Rank	0.267***	0.266***	0.268***	0.270***	0.286***	0.270***	0.265**	0.267***	0.288***
	(0.0978)	(0.0989)	(0.0984)	(0.101)	(0.0979)	(0.102)	(0.106)	(0.0999)	(0.0959)
Started Using Twitter		-0.0174	-0.0154	-0.0347	-0.0102	-0.131***	-0.0516	-0.0146	-0.111**
		(0.0426)	(0.0427)	(0.0437)	(0.0426)	(0.0458)	(0.0444)	(0.0425)	(0.0471)
Number of Tweets			-0.00264	0.0698**					0.0180
			(0.00406)	(0.0303)					(0.0302)
Number of Tweets^2				-0.0897***					-0.0627**
				(0.0336)					(0.0302)
Twitter Mention					0.0870***				0.0582**
					(0.0209)				(0.0227)
Impressions						0.132***			0.124***
						(0.0228)			(0.0262)
Sentiment							0.0492***		-0.0104
							(0.0173)		(0.0195)
Number of Followers								0.180*	0.117
								(0.0922)	(0.0992)
Other Controls	Year Indicators, Business Category, Firm Age, Employee Count, Founder Experience, Other Prior Funding								
Observations	2,880	2,880	2,880	2,880	2,880	2,880	2,880	2,880	2,880
R^2	0.292	0.292	0.292	0.292	0.296	0.300	0.294	0.292	0.302

Notes: 1. Dependent Variable is the log value of funding collected in the 2nd round of VC funding;
2. Standard errors reported; *** p<0.01, ** p<0.05, * p<0.1

Table 4. Startup Social Media Activities and Funding Outcomes

DV: **Log(2nd Round Funding)**	(1)	(2)	(3)	(4)	(5)	(6)
Method	**OLS**		**2SLS**		**Logit**	**Heckman**
Sample	All	Twitter	All	Twitter	w/ 1st R.	w/ 1st R.
log(1st Round Funding)	0.547***	0.536***	0.547***	0.525***	0.144***	0.564***
	(0.0260)	(0.0282)	(0.0232)	(0.0265)	(0.0557)	(0.0204)
Interval between Rounds	-0.00206	-0.00544***	-0.00175	-0.00500***		
	(0.00162)	(0.00209)	(0.00152)	(0.00181)		
Existing Investors' PageRank	0.285***	0.354***	0.348	0.396*	0.170***	0.380**
	(0.103)	(0.0645)	(0.230)	(0.217)	(0.0326)	(0.190)
Started Using Twitter	-0.0860*		0.255		0.591***	0.0503
	(0.0443)		(0.513)		(0.0720)	(0.0391)
Twitter Influence	0.0993***	0.0948***	0.206***	0.212***	0.181***	0.0619***
	(0.0186)	(0.0208)	(0.0484)	(0.0409)	(0.0361)	(0.0176)
Lambda						-0.0620
						(0.120)
Other Controls	Year Indicators, Business Category, Firm Age, Employee Count, Founder Experience, Website Traffic Rank, Google Trends, Facebook Presence, Other Prior Funding					
Observations	2,880	1,588	2,762	1,527	6,378	6,378
R^2	0.298	0.364	0.265	0.345	0.730	

Notes: 1. In columns (1) and (2), the dependent variable is the log of 2nd Round Funding; columns (1) and (2) report results from OLS regression; columns (3) and (4) report results using two stage least squares. Columns (5) and (6) looks at the sample of all startups that received 1st round funding. In Column (5), the dependent variable is dummy variable for whether or not the startup firm receives 2nd round VC funding, reporting results from logistic regression; Column (6) uses Heckman model, taken into consideration that startups not receiving 2nd round VC founding would not have the funding amount available.

2. Three sets of instruments in the 2SLS regression: 1) Google Trend for the keyword "Twitter" in each region; 2) Twitter usage, number of tweets and twitter influence in the other startups located in the same region; 3) twitter usage, number of tweets and twitter influence in other firms that the investors previously invested in.

3. Columns (1)(3) use all startups that received 2nd round funding, columns (2)(4) use the subsample of startup that has started Twitter page before receiving 2nd round VC funding, columns (5)(6) use all startups that received 1st round funding

4. Standard errors reported; *** p<0.01, ** p<0.05, * p<0.1

Table 5. Social Media and Number of Investors in 2nd Round VC Funding

DV: Number of Investors	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS		Negative Binomial		2SLS	
Sample	All	Twitter	All	Twitter	All	Twitter
Log(1st Round Funding)	0.328***	0.245***	0.0919***	0.0669	0.492***	0.253***
	(0.0648)	(0.0940)	(0.0325)	(0.0433)	(0.119)	(0.0914)
Interval between Rounds	-0.00608	-0.00702	-0.00164	-0.00227	-0.00163	-0.00313
	(0.00420)	(0.00592)	(0.00227)	(0.00301)	(0.00780)	(0.00626)
Existing Investors' PageRank	-0.388	-0.144	-0.150	-0.0734	0.0674	-0.0592
	(0.325)	(0.378)	(0.385)	(0.408)	(1.180)	(0.750)
Started Using Twitter	-0.317***		-0.0877		9.284***	
	(0.117)		(0.0671)		(2.659)	
Twitter Influence	0.244***	0.178**	0.0713**	0.0474	0.0889	0.543***
	(0.0631)	(0.0717)	(0.0293)	(0.0333)	(0.249)	(0.141)
Other Controls	Year Indicators, Business Category, Firm Age, Employee Count, Other Funding, Founder Experience, Website Traffic Rank, Google Trends, Facebook Presence					
Observations	2,880	1,588	2,880	1,588	2,762	1,527
R^2	0.125	0.126				0.109

Notes: 1. The dependent variable is the number of investors in the 2nd round; columns (1) and (2) report results from OLS regression; columns (3) and (4) report results using Negative Binomial Model; columns (5) and (6) report results using two stage least squares.

2. Columns (1)(3)(5) use all startups and columns (2)(4)(6) use the subsample of startup that has started Twitter page before receiving 2nd round VC funding

3. Standard errors reported; *** p<0.01, ** p<0.05, * p<0.1

Table 6. Social Media and Search Cost Reduction – Angel Investors

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	**Number of Angel Investors in 2nd Round**		**Number of New Angel Investors in 2nd Round**		**Number of Angel Investors in 2nd Round**	
Method	OLS		OLS		2SLS	
Sample	All	Twitter	All	Twitter	All	Twitter
Number of Investors in 2nd Round	0.218***	0.297***	0.177***	0.242***	0.222***	0.296***
	(0.0238)	(0.0314)	(0.0218)	(0.0289)	(0.00867)	(0.00974)
log(1st Round Funding)	-0.104***	-0.128***	-0.0777***	-0.0947***	-0.0841***	-0.138***
	(0.0226)	(0.0322)	(0.0213)	(0.0309)	(0.0284)	(0.0343)
Interval between Rounds	0.000941	0.00406*	0.00118	0.00453**	0.00214	0.00479**
	(0.00146)	(0.00224)	(0.00137)	(0.00215)	(0.00192)	(0.00235)
Started Using Twitter	0.0851**		0.0836**		1.770***	
	(0.0386)		(0.0341)		(0.408)	
Twitter Influence	0.0261	0.0174	0.0170	0.00894	0.105*	0.219***
	(0.0196)	(0.0233)	(0.0171)	(0.0208)	(0.0588)	(0.0511)
Other Controls	Year Indicators, Business Category, Firm Age, Employee Count, Other Prior Funding, Existing Investors' Page Rank, Founder Experience, Website Traffic Rank, Google Trends, Facebook Presence					
Observations	2,880	1,588	2,880	1,588	2,762	1,527
R^2	0.342	0.443	0.306	0.401	0.233	0.376

Notes: 1. In columns (1)(2)(5)(6), the dependent variable is the number of angel investors in the 2nd funding round; in columns (3) and (4), the dependent variable is the number of angel investors in the 2nd funding round who did not invest in the 1st round

2. Columns (1)-(4) report results from OLS regression; columns (5) and (6) report results using two stage least squares; columns (1)(3)(5) use all startups and columns (2)(4)(6) use the subsample of startup that has started Twitter page before receiving 2nd round VC funding

3. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Social Media and Search Cost Reduction – Investors' Investment Diversity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables	**Number of Investors with Diverse Portfolios**				**Number of Investors with Industry Focus**			
Method	OLS		2SLS		OLS		2SLS	
Sample	All	Twitter	All	Twitter	All	Twitter	All	Twitter
Number of Investors in 2nd Round	0.245***	0.279***	0.227***	0.270***	0.180***	0.0926***	0.181***	0.0948***
	(0.0157)	(0.0227)	(0.0105)	(0.0119)	(0.0177)	(0.0133)	(0.00796)	(0.00720)
log(1st Round Funding)	0.237***	0.304***	0.209***	0.298***	0.0430*	0.0333	0.0393	0.0346
	(0.0285)	(0.0414)	(0.0342)	(0.0418)	(0.0261)	(0.0280)	(0.0260)	(0.0254)
Interval between Rounds	-0.0078***	-0.0083***	-0.0079***	-0.0084***	9.79e-05	-0.00132	0.000296	-0.00116
	(0.0019)	(0.0027)	(0.0023)	(0.0029)	(0.00171)	(0.00170)	(0.00177)	(0.00173)
Started Using Twitter	0.0466		-1.752***		-0.137***		-0.930**	
	(0.0581)		(0.493)		(0.0497)		(0.375)	
Twitter Influence	0.177***	0.164***	0.588***	0.317***	-0.0702***	-0.0531***	-0.123**	-0.0828**
	(0.0271)	(0.0309)	(0.0712)	(0.0625)	(0.0188)	(0.0181)	(0.0542)	(0.0379)
Other Controls	Year Indicators, Business Category, Firm Age, Employee Count, Other Prior Funding, Existing Investors' Page Rank, Founder Experience, Website Traffic Rank, Google Trends, Facebook Presence							
Observations	2,880	1,588	2,762	1,527	2,880	1,588	2,762	1,527
R^2	0.439	0.468	0.240	0.451	0.443	0.291	0.384	0.300

Notes: 1. In columns (1)-(4), the dependent variable is the number of investors with diverse investment portfolios (i.e. in the upper 25th percentile of total number of business categories covered in previous investments); in columns (5)-(8) the dependent variable is the number of investors with industry focuses (i.e. invested in the business category before and in the lower 25th percentile of total number of business categories covered by previous investments)

2. Columns (1)(2)(5)(6) report results from OLS regression; columns (3)(4)(7)(8) report results from 2SLS regression; columns (1)(3)(5)(7)use all startups and columns (2)(4)(6)(8) use the subsample of startup that has started Twitter page before receiving 2nd round VC funding

3. Standard errors reported; *** p<0.01, ** p<0.05, * p<0.1

Table 8. Social Media and Search Cost Reduction – Startup Location

DV: Log(2nd Round Funding)	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	2SLS	2SLS
Sample	All	All	Twitter	All	Twitter
log(1st Round Funding)	0.536***	0.536***	0.520***	0.528***	0.511***
	(0.0259)	(0.0260)	(0.0284)	(0.0222)	(0.0260)
Interval between Rounds	-0.00193	-0.00188	-0.00522**	-0.00165	-0.00485***
	(0.00162)	(0.00160)	(0.00207)	(0.00148)	(0.00177)
Existing Investors' PageRank	0.299***	0.302***	0.364***	0.336	0.400*
	(0.106)	(0.109)	(0.0812)	(0.225)	(0.212)
Started Using Twitter	-0.0871**	-0.00632		-0.00222	
	(0.0439)	(0.0517)		(0.368)	
Twitter Influence	0.0915***	0.0512***	0.0413*	0.0759	0.0745*
	(0.0186)	(0.0197)	(0.0217)	(0.0575)	(0.0450)
Far from VC	-0.172***	-0.0803	-0.269***	0.112	-0.297***
	(0.0295)	(0.0515)	(0.0429)	(0.0903)	(0.0462)
Far from VC * Started Using Twitter		-0.162**		-0.494***	
		(0.0720)		(0.153)	
Far from VC * Twitter Influence		0.102***	0.122***	0.215***	0.190***
		(0.0372)	(0.0392)	(0.0737)	(0.0555)
Other Controls	Year Indicator, Business Category, Firm Age, Employee Count, Founder Experience, Website Traffic Rank, Google Trends, Facebook Presence, Other Prior Funding				
Observations	2,880	2,880	1,588	2,762	1,527
R^2	0.307	0.309	0.382	0.297	0.375

Notes: 1. Far from VC is a binary variable indicating whether the startup firm is located within the VC cluster regions of Boston, New York and San Francisco.
2. Columns (1)(2)(4) uses all the sample and column (3)(5) uses the subsample of startup that has started Twitter page before receiving 2nd Round Funding; Columns (1)-(3) report results from OLS regression; columns (4) and (5) report results from 2SLS
3. *** p<0.01, ** p<0.05, * p<0.1

Table 9. Social Media and Quality Signal – VC Syndicates

DV: Number of Experience Investors	(1)	(2)	(3)	(4)
Sample	All	Twitter Users	All	Twitter Users
log(1st Round Funding)	0.183***	0.258***	0.181***	0.254***
	(0.0211)	(0.0327)	(0.0211)	(0.0327)
Interval between Rounds	-0.00469***	-0.00539***	-0.00444***	-0.00503***
	(0.00137)	(0.00191)	(0.00137)	(0.00191)
Number of Investors	0.110***	0.125***	0.108***	0.123***
	(0.0102)	(0.0153)	(0.0104)	(0.0154)
Started Using Twitter	-0.00359		0.000800	
	(0.0393)		(0.0395)	
Twitter Influence	0.145***	0.129***	0.140***	0.126***
	(0.0205)	(0.0243)	(0.0201)	(0.0239)
VC Syndicate			-0.0146	-0.0530***
			(0.0114)	(0.0142)
VC Syndicate * Started Using Twitter			-0.0537***	
			(0.0162)	
VC Syndicate * Twitter Influence			-0.0217**	-0.0190
			(0.0103)	(0.0124)
Other Controls	Year Indicator, Business Category, Other Prior Funding, Firm Age, Employee Count, Founder Experience, Website Traffic Rank, Google Trends, Facebook Presence, Existing Investors' PageRank			
Observations	2,880	1,588	2,880	1,588
R^2	0.347	0.350	0.350	0.353

Notes: 1. The dependent variable is the number of experienced investors in the 2nd round, defined as those having made more than 100 investments up to date (top 20 percentile in number of investments made to date)
2. VC Syndicate is the percentage of investors in the 2nd round with partners from previous VC syndicates already invested in the same startup firm;
3. Columns (1) and (3) use all the sample and columns (2) and (4) use the sample of startups with Twitter page prior to receiving 2nd Round Funding;
4. Standard errors reported; *** p<0.01, ** p<0.05, * p<0.1

Appendix

Panel Regression with Fixed Effects

Another approach to control for the unobserved startup quality is to use a panel structure setup, with observations for startup-year combinations and calculating the total amount of funding the startup firms has collected up to date:

$$
\begin{aligned}
&\log(TotalFunding) = \alpha_0 + \ \beta_0 FirmAge + \beta_1 \boldsymbol{Started\ Using\ Twitter} \\
&+ \boldsymbol{\beta_2 NumberofTweets} + \boldsymbol{\beta_3 Twitter\ Influence} \\
&+ \beta_5 WebsiteTrafficRank + \beta_6 GoogleTrend + \beta_7 OtherPlatform \\
&+ business\_category + year + \varepsilon
\end{aligned}
$$

In Table A.1, we relate the log of total funding collected up to date, to the social media activities measures and the startup and entrepreneur level controls, including startup level fixed effects to capture unobserved quality (Columns 1 and 2). Results are largely consistent with before, indicating that startups present on social media, actively posting tweets and having high influence measure, are more likely to collected more funding across the years. Compared with results in Table 4, in the Fixed Effects regressions, being present on Twitter and tweeting information also positively contributes to funding outcomes. This is probably due to the accumulated effect over the years of heterogeneity across startup firms. In addition, we instrument for the Twitter activity measures on top of the Fixed Effects model, we continue to observe that startups with stronger influence on Twitter are more likely to collect larger sums of funding in total (Columns 3 and 4). The directions of the effects are consistent with before, while the scales are slightly higher compared with columns 1 and 2. This is likely due to the fact that we are already controlling for startup fixed effects and having many control variables in place, the marginal effects captured by IVs could be larger in scale. Still, the IV results indicate that we are not over-estimating the size of the effect.

Table A.1. Social Media Activities and Total Funding, Fixed Effects

DV: log(total funding)	(1)	(2)	(3)	(4)
Model	FE	FE	FE/IV	FE/IV
Sample	All	Twitter Users	All	Twitter Users
Firm Age	0.321***	0.404***	0.508***	0.368***
	(0.0143)	(0.0175)	(0.0292)	(0.0926)
Website Traffic Rank	-0.507***	-0.469***	-0.286***	0.716
	(0.0369)	(0.0397)	(0.0731)	(0.780)
Google Trends	-0.00570	-0.00885**	-0.0164	-0.0468**
	(0.00375)	(0.00386)	(0.0106)	(0.0231)
Started Using Twitter	1.340***	1.683***	-5.869***	17.26
	(0.0605)	(0.0673)	(1.046)	(21.86)
Number of Tweets	0.0219***	0.0218***	0.978***	2.348***
	(0.00591)	(0.00589)	(0.297)	(0.860)
Twitter Influence	0.766***	0.801***	2.100***	3.178*
	(0.0307)	(0.0309)	(0.520)	(1.768)
Other Controls	Year Controls, Business Category, Dummies for missing Variables			
Constant	11.36***	10.39***	7.497***	-9.711
	(0.542)	(0.581)	(1.019)	(13.25)
Observations	105,292	74,283	104,834	74,011
R-squared	0.738	0.739	18,054	13,257

Notes: 1. Dependent variable is the log of the total amount of funding collected up to date;
2. Columns (1) and (2) show results using fixed effects regression; columns (3) and (4) use fixed effects regression with instrumental variables. The instruments are: 1) Google Trend for the keyword "Twitter" in each region; 2) Twitter activities in the other startups located in the same region; 3) Twitter activities in other firms that the investors previously invested in.
3. Columns (1) and (3) uses all the sample and columns (2) and (4) use the subsample of startups that have eventually started Twitter Page
4. Robust standard errors reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1