Safety Nets? Geographic Proximity, Social Ties and the Funding of Contentious Innovation

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Abstract

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ABSTRACT

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INTRODUCTION

Social scientists have long been interested in the potential of innovation to stimulate economic growth and social advancement (Schumpeter, 1934; Solow, 1956; Wong et al., 2005). We know that the process of innovation is not necessarily smooth: Innovations can unleash “creative destruction” that can obsolete entire industries or bring down the reigning corporate titans (e.g., Anderson and Tushman, 1990; Henderson and Clark, 1990; Schumpeter, 1934). Some innovations are welcomed when they are first introduced on the market, whereas others are seen as controversial, contentious or objectionable. For example, life insurance was highly controversial at its inception in the early 19th century, vilified as an improper way to benefit financially from the death of a loved one (Zelizer, 1979); big-box retailers such as Walmart and Target have faced much opposition because of their economic impact on local small businesses (Ingram et al., 2010); and modern ride-hailing companies such as Uber have attracted the ire of privacy and labor rights advocates (Newsham, 2015; Rogers, 2015).

The ongoing emergence of such controversial innovations creates an interesting puzzle. We know that organizations are dependent on their relationships with stakeholders from the external environment in order to survive and thrive (Pfeffer and Salancik, 1978), and those who violate social expectations may fail to secure support from critical constituencies (Meyer and Rowan, 1977; Sullivan et al., 2007). Thus, the question arises: How do organizations involved in controversial innovation secure the necessary resources—the most basic of which are financial resources in the form of risk capital—in their earlier stages before they have started generating self-sustaining cash flow?

A natural starting place for investigating this puzzle is with the start-up companies that are founded to pursue the commercialization of specific innovations, and the investors that fund them. Investing in early-stage companies presents significant risks, but also the potential
of returning the investment multiple times over through an Initial Public Offering (IPO) or acquisition by an established industry actor (Gompers and Lerner, 1999). Even if venture investors are rationally minded value maximizers, unconstrained by tradition or value judgments, they have to weigh the potential risks of investments in controversial start-ups carefully. Even for established corporations, controversial practices, products, and business models can have quantifiable effects on survival, performance and financial valuations (e.g., Fauver and McDonald, 2014; Kim and Venkatachalam, 2011; King and Soule, 2007; Ruef and Scott, 1998); the price of illegitimacy can be even steeper for new ventures, which are especially dependent on stakeholder buy-in and for whom conformity with the institutionalized norms can be a matter of life and death (e.g., Delmar and Shane, 2004). Additionally, investors in potentially controversial start-ups face legitimacy risks in addition to the financial risk associated with the investment. In other words, objectionable start-ups may damage the reputation of the investors and others who are associated with the startup (Tian et al., 2016). A negative reputation, in turn, could potentially hurt other companies in the investors’ portfolios and make the investors less attractive to future start-ups that are seeking investment (Drover et al., 2014).

In this paper, we examine how investors navigate the risks they face when investing in companies that customers or other stakeholders are likely to see as objectionable or controversial for some reason. Investors have at least two options when dealing with the additional risks presented by such businesses. They can seek out additional, often tacit, information about the start-up before investing, that can help them judge the severity of the issue and predict whether the objectionable nature of the business will have negative implications in the future. They can also ensure that they can monitor the activities of the business after investing, emphasizing in particular monitoring that goes beyond financial
monitoring, and to a greater extent than they might for a non-controversial with similar cost and revenue prospects.

There are several ways in which they can achieve these goals. In particular, they might rely on geographic proximity between the location of the investor and the start-up, which facilitates both pre-investment information gathering (e.g., Sorenson and Stuart, 2001) and ongoing monitoring through more frequent on-site meetings and visits (e.g., Bernstein et al., 2016). They might also rely on both weak and strong network ties for gathering tacit information about the business. Network ties, in particular relatively strong ones formed by prior co-investment relationships, may also be valuable in monitoring the business and enforce any actions that the investors might wish the business to take to mitigate its objectionable nature (Hallen, 2008; Shane and Cable, 2002). In other words, while geographic proximity and social ties are important for facilitating investments in general (cf. Sorenson and Stuart, 2001), they are especially crucial for alleviating investor concerns about investing in contested innovations.

To examine these predictions empirically, we have assembled a dataset using information gathered from third-party raters: Individuals received a short description of a company’s core business activities and were asked to estimate how objectionable the core business of the said company was. We used Amazon’s Mechanical Turk (AMT) micro-labor service to collect data, where individuals recruited through the service were given a description of the company business, then asked to evaluate the likelihood that people would object to the activities of the company. Overall, AMT can be used to obtain high-quality data rapidly and at a low cost, and the results have been found to be reliable in social science research settings (Buhrmester et al., 2011; Huff and Tingley, 2015). We link this dataset with data on venture investments in these companies, as well as with data on other investments by
the VC firms, in order to explore the geographical and social patterns associated with investments in controversial innovations.

THEORY AND HYPOTHESES

The idea that organizations have to conform to social expectations has deep roots in organizational theory. Institutional theorists have long believed that legitimacy being “[the] generalized perception or assumption that the actions of an entity are desirable, proper or appropriate within some socially constructed system of norms, values, beliefs, and definitions” (Suchman, 1995:574) is a major strategic resource of organizations. Actors that overtly deviate from the established norms are considered illegitimate and less likely to be able to access the external endorsement and resources necessary for organizational survival and success (DiMaggio and Powell, 1983; Hannan and Freeman, 1984; Meyer and Rowan, 1977). For example, hospitals that fail to conform to expected managerial practices suffer from poorer assessments (Westphal et al., 1997) and diminished chances of survival (Ruef and Scott, 1998). Legitimacy concerns are important to new ventures as well and have been shown to impact their founding and subsequent survival (Delmar and Shane, 2004; Tornikoski and Newbert, 2007).

When an innovation is first introduced, it is new to the world and by definition lacks institutional legitimacy, since institutional legitimacy derives in part from the history of a particular practice or organizational form (Carroll and Hannan, 2000; McKendrick and Carroll, 2001). Not all innovations, however, are equally threatened by this lack of legitimacy. Some innovations are seen as neutral and eventually gain legitimacy in an uncontroversial manner, simply through adoption and history of use. In other cases, individuals and groups may see the innovation as more or less objectionable, because it violates specific norms or is seen as repugnant (Rogers, 2015; Roth, 2007; Zelizer, 1978).
Some controversial innovations eventually establish their legitimacy. For example, life insurance policies were initially derided as “the capitalization of affection” (Zelizer, 1978: 594), a clear violation of norms regarding the sanctity of life and norms regarding benefitting from the harm of others. The framing of this innovation in relation to these norms changed over the years (partly through the advocacy of those involved), and purchasing life insurance, which was once seen as controversial and even sacrilegious, is now seen as a responsible and uncontroversial aspect of financial family planning. (Zelizer, 1978). This process takes time, however, and it is not always clear at the outset how it will unfold. Uber, for example, has made itself many enemies as a result of its aggressive business model, even though it is in the relatively uncontroversial commercial transportation industry. When moving into a new city, Uber has generally attempted to bypass existing taxi organizations and unions as much as possible, signing up individual drivers that are not licensed or vetted by anyone other than Uber itself. This model has made Uber popular among customers, but much loathed among taxi drivers, labor rights advocates and others (Newsham, 2015; Rogers, 2015). Despite this controversy, there are signs that the company is increasing its alignment with social norms, both through adaptations of its own business and the evolution of the norms themselves. And if this process is successful, the investment in Uber will be very profitable for its investors, which include blue-chip firms such as BlackRock, Fidelity Investments and Kleiner Perkins Caufield & Byers.

Other innovations are, after an initial period, permanently relegated to the illegitimacy side of the continuum. Digital spam originated when a marketing manager at Digital Equipment Corporation sent out an unsolicited mass email to 393 recipients over the Arpanet, marketing a new computer system (Abate, 2008). Although spam persists to this day because of the associated economics, it is now generally seen as being an illegitimate business activity. Similarly, the online site Ashley Madison, which was explicitly designed to facilitate
extramarital affairs for married people, attracted much controversy when a security breach brought it into the public eye and has faced ongoing commercial problems since (Thielman, 2015).

While there is a long tradition on the pressures for conformity that companies face (Delmar and Shane, 2004; DiMaggio and Powell, 1983; Ruef and Scott, 1998), in part because organizations that do not conform to their environment are more likely to be starved for resources (Pfeffer and Salancik, 1978), the fact remains that some organizations do secure the resources to survive and thrive. So, our central question is: What assurances do investors need in order to put resources into such organizations?

While there are a variety of ways to access capital—friends and family, angel investors, crowdfunding platforms—venture capital remains a critical source of funding for ambitious companies looking to quickly scale up their business (Gompers and Lerner, 2001). Venture capitalists bring a variety of tools—such as extensive due diligence, staged investments, high-powered incentives, and close monitoring, often via board membership—specifically designed to deal with the high uncertainty and asymmetric information that pervades early-stage opportunities (Gompers, 1995; Gompers and Lerner, 1999). At the same time, they offer more than just financial capital: they are often quite involved in the ventures they invest in (Ehrlich et al., 1994; Jääskeläinen et al., 2006; Sapienza et al., 1996), contributing their knowledge, experience and networks while certifying its quality to external audiences (Hsu, 2004; Lee et al., 2011; Stuart et al., 1999).

Venture investments tend to occur through syndications: joint investments of multiple investors in a particular start-up. Syndications help pool both the hard assets (capital) and soft assets (experience and networks of the individual VC investors) of the investors, while spreading risks of failure (Hochberg et al., 2015; Jääskeläinen et al., 2006; Lerner, 1994). The lead partners of the syndicating venture investment firms typically sit together on the portfolio
company’s board to advise the entrepreneur and provide access to their networks (Gorman and Sahlman, 1989). Such close collaborations can create lasting relationships between the venture capitalists involved. Prior syndication ties lead to referrals and information about potential investment opportunities, and the network formed by these relationships has been shown to affect a variety of important outcomes such as the spatial distribution of VC investments (Sorenson and Stuart, 2001), the selection of syndication partners (Sorenson and Stuart, 2008; Zhelyazkov and Gulati, 2016) as well as the performance of venture capital firms (Hochberg et al., 2007).

**The matching process of investors and objectionable start-ups**

The process of venture investments is inherently a matching process between the start-ups that seek funding and the investors who are looking to provide it. There are many issues for both parties to consider. The entrepreneurs take into account the valuation that the investor is willing to give to the business and the funding amount, but they also consider whether the investors are likely to be able to assist in future funding rounds (Zhelyazkov and Gulati, 2016), whether they might facilitate synergies with other companies in their portfolios (Lindsey, 2008), as well as whether they have the reputation to effectively certify the quality of the start-up to external audiences (Hsu, 2004; Stuart et al., 1999). Investors look to assess the financial attractiveness of the venture, often using signals such as awards, achieved milestones and human capital of the founders (e.g., Hallen, 2008); in addition they also consider how the venture relates to their industry focus and investment experience (Dimov and de Holan, 2010; Gompers et al., 2009) and the confidence they have in the remaining syndication partners' capabilities and motivations (Sorenson and Stuart, 2008; Zhelyazkov and Gulati, 2016).

When the business model of a start-up is potentially objectionable, this introduces additional considerations into the matching process. Even if potential investors do not
themselves have any inherent objections to the practices of the start-up, they will need to consider how other stakeholder’s reactions can create inherent risks for the venture and its investors. First and foremost, there are the direct business risks to consider. Organizations that do not cleanly conform to the norms and expectations of their environment face a greater risk of failure (e.g., Delmar and Shane, 2004; Hiatt et al., 2009; Ruef and Scott, 1998); even those that survive can face stakeholder resistance that can undermine their operations in various ways such as protests (Ingram et al., 2010), consumer boycotts (McDonnell and King, 2013), or avoidance by other stakeholders such as prospective alliance partners (e.g., Sullivan et al., 2007). All in all, this has negative implications on the financial valuations that controversial organizations can achieve in the financial markets, to the detriment of their investors (Kim and Venkatachalam, 2011; King and Soule, 2007).

Second, it is possible that the investors themselves might expose themselves to legitimacy risks by investing in companies with potentially objectionable business models. It is well established that illegitimacy can affect those who are in some way associated with an illegitimate party. Such associations might be merely due to similarity to a controversial party (e.g., Jonsson et al., 2009), but stigma can be even more easily transmitted through freely chosen relationships. For example, firms suffer diminished valuation on the financial markets as a result of their suppliers’ corporate social responsibility violations (Rogers, 2016); and venture capital firms that fail to prevent fraudulent behavior by their portfolio companies have a harder time taking their other companies to market or securing funds from limited partners (Tian et al., 2015).

For all these reasons, when investors are evaluating start-ups whose operations may be controversial or seen as objectionable by customers or other stakeholders, they are especially likely to try to seek to counter the risks inherent in such investments by reducing uncertainty in other ways. There at least two general approaches to reducing that uncertainty: ex-ante and
ex-post. Ex-ante, an investor may seek to gather more information from various sources about the investment opportunity, in order to better understand if and how potential controversial practices would influence stakeholders in the future. In gathering such information, an investor may seek to learn more about the start-up itself and its business model, in order to understand how future developments in the development of the start-ups offering and subsequent scaling will affect it. Such due diligence may allow the investors to understand better how crucial any particular objectionable aspects are to the business model as a whole, and whether they are likely to become more or less salient with time. By consulting a variety of sources, the investor can also learn how different actors perceive the potentially controversial practices; by learning more about how third-party stakeholders view the company, they may be able to better evaluate the risk that the nature of the business model will jeopardize the start-up's relationship with such stakeholders in the future.

Ex post, an investor who is looking to invest in a potentially objectionable start-up may look for ways to better monitor it after investing. On-going monitoring is a key activity of all venture investors (Gorman and Sahlman, 1989; Jääskeläinen et al., 2006; Macmillan et al., 1989), and there are multiple ways in which it can alleviate the risks posed by objectionable start-ups. Any adverse consequences of the controversial innovations pursued by the start-up may only materialize later on, when it needs to forge new relationships with important stakeholders, or when it faces protests or other collective action. By monitoring the activities of the start-up, investors may be able to foresee any issues and support the start-up in dealing with them. Investors may also want to be proactive in suggesting alternative, and less controversial, ways of implementing certain aspects of the business model based on an on-going evaluation of the potential reactions of other stakeholders.

Various things affect how effective these two approaches will be for an investor who is considering a particular venture investment. Geographic proximity between the investor
and the target company increases the probability of start-up investments in general (Sorenson and Stuart, 2001), and may be especially relevant for investors who are considering the risks associated with investing in potentially objectionable start-ups. Geographic proximity facilitates information gathering about a start-up before investment in several ways (Malloy, 2005; Sorenson and Stuart, 2001). To the extent that the existing market of the start-up has some geographic concentration, an investor will find it easier to learn about their opinions and the opinions of other affected parties. Due to the spatial organization of networks, a geographically proximate investor will also be more likely to know trusted mutually connected third parties with tacit knowledge about the potential legitimacy risks associated with the company.

After investing, several practical characteristics of geographic proximity facilitate ongoing monitoring of the start-up (Bernstein et al., 2016). Monitoring occurs in part by evaluating financial results and product development milestones but also on observing the day-to-day activities of the firm and the interactions between its founders, employees and other stakeholders (Fried and Hisrich, 1995). Being located in the same area makes it much simpler for investors to attend meetings in person which facilitates such observations. Investors also have more opportunities to visit the premises of the start-up, which gives them a richer view of the evolution of the start-up and allows them to interact with other employees than the founders. And should any unforeseen circumstances come up, investors will find it easier to provide support and advice at short notice to start-ups that are located nearby than if they are a plane-flight away. Taken together, these considerations suggest that geographic proximity will have an impact on the investment matching process for potentially objectionable start-ups, above and beyond the impact that it has in general. Specifically, we expect the following hypothesis to hold true:
Hypothesis 1: Having a business model that is likely to be seen as objectionable reduces the relative probability a start-up will receive investment from geographically distant investors.

Investors can also rely on their networks for better understanding potential legitimacy risks that a particular investment opportunity presents. A long tradition in organizational theory has identified prior relationships as important builders of trust that facilitate future collaboration (Gulati, 1995a; Gulati, 1995b; Gulati and Gargiulo, 1999; Li and Rowley, 2002; Uzzi, 1996, 1997). In particular, relationships formed with other investors through prior syndications with other venture investors are likely to prove very useful in alleviating the concerns about risky opportunities (Meuleman et al., 2010; Sorenson and Stuart, 2001; Zhang et al., 2017). Those investors are likely to have experience in judging the risks associated with venture investments and understand the considerations that the focal investor must consider. Because such direct ties tend to involve relatively frequent interaction, for example through mutual board memberships, they also facilitate rapid and trusted information transfer (Zhelyazkov and Gulati, 2016). If a prior syndication partner is familiar with the start-up in question, that investor can provide important additional information about specifics related to the operation of the startups, helping to evaluate to what extent controversial aspects of the business can be mitigated. A potential investor is likely to value such information when considering any investment but may find the opinion of a trusted prior co-investor especially valuable when trying to judge complicated considerations such as legitimacy risks.

Should the investment go forward, such ties also simplify the ongoing monitoring of the start-up. With a familiar and trusted syndication partner sharing the monitoring responsibilities, an investor may feel greater assurance that any issues will be communicated to them (Meuleman et al., 2010; Sorenson and Stuart, 2001; Zhang et al., 2017). If both investors join the board of the company, the familiarity may promote frank and honest discussions in the board work, and if only one investor is on the board, ties of trust will
provide assurance to the other investor. Furthermore, direct ties between investors will facilitate agreement on any necessary action to address emerging threats (Zhang et al., 2017).

Based on this reasoning we present the following hypothesis:

Hypothesis 2: Having a business that is likely to be seen as objectionable increases the relative probability that a start-up will receive investments from investors who have prior direct ties to other investors in the start-up.

A third way in which investors may be able to reduce the legitimacy risks associated with potential investment target is through indirect ties with other investors, that is, ties formed through investments with a mutually shared syndication partner (Zhelyazkov and Gulati, 2016). Such ties do not provide as strong a relationship as direct prior co-investment experience, but their reach is potentially greater and so they may be especially useful in constructing a detailed perspective on the activities of the business, its likely future direction, and the attitudes of a wide variety of stakeholders or potential stakeholders (for a related argument in the alliance setting, see Gulati, 1995b; Gulati and Gargiulo, 1999). Indirect ties may, therefore, be particularly relevant for the initial evaluation of a potentially objectionable startup.

When it comes to post-investment monitoring, indirect syndication ties do not provide as clear benefits as direct ties forged through collaboration between investors on specific prior start-ups. It is therefore mainly due to their potential role in the pre-investment information gathering about the startup and the perspectives of other stakeholders that we present the third hypothesis about such ties:

Hypothesis 3: Having a business that is likely to be seen as objectionable increases the relative probability that a start-up will receive investments from investors who have prior indirect ties to other investors in the start-up.
DATA AND METHODS

Data Sources
To test our hypotheses, we integrated two major sources of data. For data on VC investments, we utilized the VentureXpert database maintained by Thompson Reuters. It provides detailed information at the level of the investment round on VC-backed portfolio companies and their investors, as well as information about VC investments in over 16,000 start-up companies. Since multiple VCs often invest together (through syndicates), and since start-ups often require several rounds of funding, each start-up is typically associated with between 5 and 20 investment decisions by VCs. In all, the database we utilized contains information about over 150,000 individual investments in the period between 1980 and 2008. We included US-based start-ups in our analysis, both to ensure institutional homogeneity and because the VentureXpert database information on US-based start-ups is richer for individual start-ups, which we utilized for constructing our measure of the strength of objection to each start-up. Following the typical practice of prior research, we also focused on US-based investors only (e.g., Zhang et al., 2017). This database has been extensively used by both finance (Hochberg et al., 2007, 2010) and organizational scholars (Podolny, 2001; Sorenson and Stuart, 2001, 2008; Zhelyazkov, 2018; Zhelyazkov and Gulati, 2016).

To determine the extent to which a start-up’s activities are potentially controversial or objectionable, we relied on evaluators recruited through AMT, an online marketplace for micro-labor. The original data that we used to evaluate the strength of objection to start-ups’ business activities comes from Thomson Reuter’s VentureXpert database. From this data set, we extracted all firms that had VC investments and also a written firm description. In total, 16,865 firms had a written description, which accounts for the vast majority of US companies in the database. Evaluators were asked to read descriptions of the business activities of start-ups and determine whether those activities could be considered objectionable. We gave the evaluators no information about the purpose of the research project, only the written
description of the firm from the start-up database. We then submitted questionnaires that included the company descriptions to individuals recruited through AMT. These individuals got paid a small compensation to evaluate the companies. Buhrmeister et al. (2011) evaluated the quality of data collected using AMT in the context of social science experiments and found its reliability to be comparable to data collected in more traditional settings. Since AMT makes it simple and economical to solicit responses from a large number of evaluators, it is a practical way to achieve the greatest possible coverage of start-ups.

In gathering the data, we focused on industries that are not likely to be seen as controversial in and of themselves. In preliminary data collection, we found that raters tended to rate companies within certain industries as potentially objectionable mainly because of the association with the industries themselves. We saw this occurring in particular with companies within the industries of oil and gas, mining, biotechnology, and genetic engineering. Although this is not an issue in and of itself (the practices of firms within those industries are indeed more likely to be seen as controversial than in other industries), it is likely that there are other differences between firms that operate within those industries and those that do not, which would make comparison more difficult. To best utilize our available resources, we decided to focus on industries that are not controversial in and of themselves, and we excluded companies operating in those and closely related industries, based on North American Industry Classification System (NAICS) codes.

Because measuring the strength of objection measure requires that multiple individuals examine the written description of each start-up and evaluate how objectionable it is, and because we need a large sample of firms to find a meaningful number of objectionable firms, the coding procedure is a significant task. However, the efficiency of the AMT service lowers the cost of coding, making it possible to construct the measure for a much larger sample of start-ups than would be possible using conventional coding methods. For the data
set used in the analysis, we had raters evaluate the descriptions of 3,554 randomly selected start-ups (out of the total 16,865 companies with a description in the entire database).

**Analytical approach and dataset construction**

The objective of our empirics is to model the matching process between VC firms and portfolio companies; i.e., which VCs invested in a particular company out of all the VCs that could have potentially invested in that company. Factual-counterfactual logit models are a popular approach to modeling such investment decision (Sorenson and Stuart, 2001, 2008; Zhelyazkov, 2018). Our starting point is the factual VC-portfolio company dyad: the first time that an investor participated in a fundraising round of a portfolio company. Our 3,554 distinct portfolio companies were funded by a total of 11,454 distinct investors, or slightly more than three investors per company. Our next step was creating the counterfactual investors. In line with prior research, for each factual dyad, we first created a universe of all counterfactual dyads involving the focal company investment round and investors that were active at the time (i.e., invested in other companies fundraising in the same time). Altogether, the 11,454 factual company-investor-investment round pairings were matched by 6,766,204 possible counterfactuals. To reduce autocorrelation and truncate the sample down to more manageable size, we took a random sample of ten counterfactuals for every matched counterfactual (cf. Sorenson and Stuart, 2008): so our overall sample included 11,454 factual and 114,540 counterfactual observations, for a total of 125,994 observations.2

We then ran a conditional logit model grouped on the company investment round to distinguish between the investor that ultimately joined the round versus the counterfactual investors. An attractive feature of the conditional logit design is that it involves implicit fixed

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1 We do not consider the reinvestment decisions – i.e., the repeat participation in subsequent rounds – as it is a common expectation that VC firms continue investing (Zhelyazkov and Gulati, 2016), and any withdrawals are subject to different types of decision-making processes (Guler, 2007).

2 The results we report are not sensitive to the number of counterfactuals selected, and were robust to five or fifteen counterfactuals, as well as using the entire counterfactual universe. We also verified the robustness of our results by constraining counterfactuals to represent VCs that invested in the same industry as the focal company.
effects for all group invariant variables. This means that all features of the company at the
time of the investment round were effectively accounted for by the model and cannot be
explicitly included in the regression. The only variables that differ between groups are
variables associated with the identity of the investors – for example, monadic characteristics
such as investment track record, and dyadic characteristics such as geographic distance from
the company and level of specialization in its industry. We should note that the key
moderating variable in our analysis – the level of objection to the portfolio company’s core
business activities – is also invariant within groups and thus its main effect cannot be
explicitly modeled; however, we can still model its moderating effect on variables that do
vary within groups, such as the ones proposed in Hypotheses 1-3.

Key Variables

*Moderator Variable.* We constructed our key moderator—the company objection score—by
asking our Mechanical Turks raters to read a description of each company’s core business
activities and answer the question: “How likely is it that people will find the activities of this
firm objectionable?” The evaluators assigned the companies a rating using a scale ranging
from “not objectionable” to “very likely to object.” Responses of “not objectionable” or “few
people are likely to object” were assigned a score of zero, indicating that the activities of the
company were not likely to be seen as controversial or objectionable. A response of “some
people might object” received a score of one; “people are somewhat likely to object” received
a score of two; and “people are very likely to object” received a score of three. For each
company, we collected the responses of five different raters, and using that input we
calculated the overall Strength of Objection to Start-up by summing up the scores of the raters
(further details about the questions and coding procedure can be found in the appendix).
Within the sample, the variable ranged from zero to twelve (the theoretical maximum is 15,
but no company in our sample received that score).
**Independent variables.** To test Hypothesis 1, we followed the procedure outlined in Sorenson and Stuart (2001) in calculating the spherical distance between the portfolio company and the investor by using the longitude and latitude of their address registration ZIP codes (logged to decrease the dispersion). Prior research suggests that this variable has a large negative effect on investment selection, i.e., VCs are much more likely to pick geographically proximate companies (e.g., Sorenson and Stuart, 2001; Trapido, 2007); based on Hypothesis 1, we expect this preference to be even stronger for investments expected to be controversial.

To test Hypothesis 2, we follow prior research in calculating the logged average number of direct ties between the focal investor and the remaining investors in the syndicate, defined as the number of distinct companies that they have coinvested in over the preceding five years (Sorenson and Stuart, 2008; Zhelyazkov and Gulati, 2016). We calculated this measure for each dyad involving the focal investor and a pre-existing investor in the company and averaged it across all dyads. There is extensive evidence that presence of a past coinvestor alleviates VCs’ concerns about investing in the company; our Hypothesis 2 anticipates that investors particularly need such reassurance when the potential controversiality of the investment is higher. For Hypothesis 3, we use the logged average number of indirect ties between the focal investor and other syndicate partners, defined as the number of shared syndication partners that the two investors have had over the preceding five years.

**Control variables.** We included several controls for the monadic characteristics of the focal investor that may affect its levels of investment activity. First, we calculated the logged number of investments of the focal investor, defined as the number of distinct companies it has invested in over the preceding five years. This can indicate overall investment capacity of the investor and such variables are often used as a key component of prominence or reputation measures within the venture capital ecosystem (e.g., Lee et al., 2011). We control
for the *number of funds that the focal investor has raised* over the preceding five years, as they can serve both as a signal of quality and provide capital to be allocated to investment opportunities. We also account for the *focal investor’s IPO rate*—defined as the proportion of companies backed over the preceding five years that went to IPO—as a major driver of its attractiveness as an investor (Pollock et al., 2015). Finally, we calculated the *focal investor’s eigenvector centrality* in the VC syndication network, as it can be construed as a measure of its status (Podolny, 2001; Pollock et al., 2015) and also its ability to tap information about investment opportunities flowing across the network (cf. Gulati and Gargiulo, 1999; Sorenson and Stuart, 2001).

At the dyadic level, we account for the main effect of the three independent variables underlying Hypotheses 1–3: geographic distance between the focal investor and the company, as well as the number of direct and indirect ties between the focal investors and the remaining coinvestors in the company. Besides, we also control for the level of investment specialization of the focal investor in the industry of the company, defined as the proportion of distinct companies in the focal company’s industry that it has invested in over the prior five years, relative to the overall number of companies backed over the same period.3 As VC firms often specialize by industry they are more likely to pick companies of the same industry as their prior investments (Gompers et al., 2009).

**RESULTS**

Table 1 presents the univariate statistics for the key variables in our model. We have also split the factual observations (i.e., investment relationships that actually occurred) from the counterfactual observations in order to get preliminary ideas of the main effects of the different variables on tie formation. Not surprisingly, the univariate comparison between the

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3 Throughout, we define industry based on VentureXpert’s nine industry categories.
two samples suggests that large and high-status investors are especially more likely to invest in portfolio companies. Furthermore, all the dyadic variables—the level of investor specialization in the industry, geographic distance, as well as direct and indirect ties—differ widely between the factual and the counterfactual samples. We should also note that the objection score univariate statistics are the same across all subsamples: this is by construction, as the focal portfolio company (and all variables associated with it) is the same across both the factual observation and all ten counterfactual observations associated with that group.

The intuition is largely confirmed as we turn our attention to the correlations between the dependent variable and the independent variables presented in Table 2 (to save space we have presented the correlations across the entire sample; the factual and counterfactual subsample observations are available on request). While some of the independent variables are relatively highly correlated with one another, on the whole multicollinearity is not a significant concern: the highest variance inflation factor (VIF) in our regressions was 3.2, and the mean VIF was invariably under 2. Both values are significantly below the maximum value of 10 suggested by methodological research (e.g., Kutner et al., 2004)

Table 3 presents the conditional logit model. Model 1 serves as a baseline and includes the main effects of both the independent and control variables. The distance between the investor and the portfolio company, the level of investor specialization and the presence of direct ties are all powerful predictors of whether an investor would join the investment round. Interestingly, indirect ties lose significance in the model once we account for the direct relationships between the focal investor and the pre-existing investors. Model 2 finds that the already important negative effect of distance on the likelihood of tie formation is even further heightened when the portfolio company is controversial, consistent with the predictions of
Hypothesis 1. Similarly, Hypothesis 2 receives support from Model 3, which shows that direct social ties have stronger effects in the case of more controversial companies. The standalone interaction between indirect ties and the objection score shown on Model 4 is also significant, which is consistent with Hypothesis 3; however, this effect does not persist in the fully saturated specification in Model 5. Overall, the effects of direct ties seem to completely crowd out both the main and moderating effects of indirect ties through all of our specifications. This finding suggests that the social proof and greater trustworthiness of the information transmitted through such direct communication channels trumps the general awareness of opportunities that is more likely to be transmitted by indirect ties. In summary, we do not find robust enough support for Hypothesis 3. Model 6 represents our final model with both robust interactions.

[Insert Table 3 around here]

In general, there are two difficulties to directly interpreting the results of a conditional logit model as presented in Table 3. First, in a limitation shared across all nonlinear model families, the marginal effect of an interaction depends on the values of all the other variables (Hoetker, 2007; Zelner, 2009). Second, the conditional logit model presents its own unique set of issues, as it outputs the utility scores associated with a particular observation, which are only interpretable within the context of the respective factual-counterfactual group. While such a utility score can help determine which is the likely factual observation associated with the counterfactual, it cannot be used to map to any specific probability of selection for any observation.

To get around both problems, Table 4 replicates the analyses in Table 3 using a fixed effects linear probability model (again with fixed effects and standard errors clustered around the same groups as used in the conditional logit model). In such analysis, the magnitude of all coefficients is interpretable as the marginal change of probabilities, keeping in mind that the
baseline matching probability when all variables are held at their means is approximately 9% (i.e., one in eleven chance). While the magnitude of the coefficient estimates is naturally very different from the conditional logit, the direction of the effects is consistent, and the level of statistical significance is generally higher. According to Model 3, one standard deviation increase from the mean level of the logged geographic distance between the portfolio company and the investor is expected to reduce the expected matching probability by 5.9 percentage points for a company with an objection score of 0 (approximately 30% of the sample); it lowers the probability by 6.3 percentage points for companies that are at the median level of objection score (equal to 2) and lowers it by 6.9 percentage points for companies that are at the 95th percentile of the objection score range (equal to 6). Similarly, according to Model 4 a change of the mean number of direct ties from the mean value down to zero reduces the probability of tie formation from by 3.6 percentage points for noncontroversial companies, but 4.5 percentage points for highly controversial (i.e., 95th percentile) ones.

We conducted a wide variety of additional analyses that confirmed the general robustness of the results. As noted, the results are not sensitive to different functional forms (conditional logit versus fixed effect linear probability models); different ratios of factual and counterfactuals (1:5, 1:15 or keeping the entire counterfactual set); and narrower definitions of the counterfactual set (i.e., restraining the counterfactuals only to investors that have invested in the same industry as the focal company in the focal year). The results are also consistent irrespective of the specific investor-level monadic controls and replicate even in the complete absence of any of those controls.

4 Such probabilities are entirely additive; if we assume the baseline probability to be 9.1% this means that the predicted probabilities would be 3.2%, 2.8% and 2.2%, which are substantively very large differences.
Post hoc analysis: the role of the investment stage

One key contingency that stems readily from our theorizing is the degree to which the level of maturity of a portfolio company would affect the key interactions in our model. A key reason why investors would seek the reassurance of geographic proximity and pre-existing social relationships when dealing with potentially objectionable companies is that the risk of controversy can undermine their potential chances of a successful exit. However, the uncertainty created by objectionability is much larger earlier on in a company’s development, when the company is most vulnerable to the liability of newness (Freeman et al., 1983). Conversely, companies that are at a later stage in their lifecycle have already demonstrated that they are capable of surviving and thriving despite concerns about their business model, and there is more information available about specific reactions from various stakeholders to the specific objectionable aspects of their business. VentureXpert classifies rounds into four categories: seed stage, early stage, expansion stage, and later stage. We, therefore, considered whether the effects we observe would be strongest for the youngest companies (those in a seed stage) relative to more mature ones.

Table 5 presents the results of this analysis using a conditional logit similar to our main analyses. Model 1 reproduces our final specification (reported on Model 6, Table 3) for reference. Models 2 and 3 split the sample between seed-stage investment rounds and all other investment rounds. Our hypothesized results are much stronger in the seed stage sample versus the rest: for example, the interaction between objection score and distance is about four times stronger (point estimate -0.026 versus -0.006), and the interaction between objection score and prior indirect ties is about three times stronger (point estimate 0.098 versus 0.034). We verify the statistical significance of the difference of both interactions between the two samples in a fully saturated three-way interaction specification reported on Model 4 (both triple interaction coefficients are significant at the p<0.05 level).
DISCUSSION AND CONCLUSIONS

In this study, we examine how a potentially objectionable or controversial business model affects the matching process with investors that occurs when a start-up seeks funds to develop their offering and bring it to market. In particular, we suggest that to counter the potential legitimacy risks associated with such start-ups, investors who are considering investing in them are likely to rely on tacit information about the investment targets to an even greater extent than when considering non-controversial opportunities. In their decisions, investors may also consider, even more closely than usual, how well-equipped they are to provide ongoing monitoring of the start-up after the investment. We hypothesize that factors that make such tacit information gathering and post-investment monitoring more feasible for investors will make it relatively more likely that a given investor will be matched with a focal startup in the funding process. Our analyses of investments in a randomly selected sample of 3,554 start-ups provides support for two of the three such factors we consider, namely geographic proximity to the target company and direct ties with other investors in the company formed through prior co-investment. Our analyses do not consistently support the third factor, the indirect ties among investors formed through syndicate memberships with a shared third investor.

Ours is the first study to use independent raters to measure the objectionability of a large number of ventures and then analyze the result in the context of the funding process for those ventures. It is nevertheless worth noting that due to data collection constraints we focused on a random subsample of the start-ups that received funding, rather than an exhaustive universe of all controversial investments. While this approach yields valuable insights as to the equilibrium outcome of the matching process, future research that collects data on a broader section of the investable universe can develop a more sophisticated model that accounts for the outside options on both sides in the deal (Mindruta et al., 2016) and
analyzes diffusion and dynamic patterns in the matching process, thus adding further insight on the role of venture contestedness in the VC funding process.

One such potential set of questions relates to the different reasons that lead these start-ups to be seen as objectionable and how those might differentially affect VCs. In this paper, we focused on the strength of objection as a one-dimensional construct, but different groups may focus on different aspects of a business when making a judgment about its legitimacy risk (Ertug et al., 2016; Fisher et al., 2017; Lamin and Zaheer, 2012). In the context of controversial business models, stem cell research may be controversial for certain religious audiences, the primary objection to Uber comes from labor rights advocates, and social networking companies often face privacy critics. Future research could add greater nuance in the measure of controversiality; for example, one could distinguish between different audiences that may find a particular start-up objectionable and trace out the consequences of violating the expectations of particular constituencies but not others (cf. Lamin and Zaheer, 2012).

Two results from our analysis that we had not specifically hypothesized about may also merit future study. First, although our data did not allow us to measure the specific mechanisms that lead investors to be more or less likely to be matched with a given objectionable start-up, we posited that pre-investment gathering of tacit information about the start-up, and ongoing monitoring post-investment might be important elements. The two factors that received support for our analysis, geographic proximity to the start-up and direct ties among the investors, are likely to support both pre-investment information gathering and post-investment monitoring. The third factor, indirect ties among investors, which was not supported by the analysis, would be expected to support pre-investment information gathering from a wide range of stakeholders or potential stakeholders, but not necessarily support post-investment monitoring to any great extent. This result could suggest that the ability to
effectively monitor a potentially objectionable investment is the more important mechanism of the two. It may, however, also be the case that the pre-investment information gathering is the key mechanism, but that the information that investors seek needs to be validated by the greater social proof and trustworthiness of direct ties or highly embedded geographic ties, rather than the further-reaching but weaker indirect ties.

Second, our post hoc analysis examining the role of the investment stage showed that the results are stronger for early rounds of funding than for later rounds. This may indicate that when companies pursue their later rounds of funding, it is not as important to investors to utilize geographic or co-investment networks to gather information and support monitoring of the start-up. A possible reason for this finding is that at the later stage in their lifecycle, companies have demonstrated that they can effectively deal with concerns about their business model and that they can survive despite such concerns. There may also be more information available to investors about the reactions of various stakeholders to specific objectionable aspects of the business, and it could be the case that as more information about the company is available—because of longer histories of production, costs, and revenues—the weight assigned to specific aspects of its business model are less salient to investors. Our data do not provide detailed information about how exactly this process unfolds, but it may provide an interesting context for further research.

Our study makes several important contributions. While prior work has largely focused on the sources of resistance against controversial innovation, such as protest movements or legal actions (Hiatt et al., 2009; King and Soule, 2007; McDonnell et al., 2015), our work focuses on the sources of support of such innovations. We also contribute to the rich research on networks in the venture capital setting (Meuleman et al., 2010; Sorenson and Stuart, 2001, 2008; Zhang et al., 2017; Zhelyazkov and Gulati, 2016) by establishing how prior ties and geographic proximity constitute critical social safety nets to reassure investors
before they plunge into investing in controversial companies in their earliest stage, when they are especially susceptible to the liability of newness and when the full extent of the challenges they would face down the road is not as apparent.

We also contribute empirically by operationalizing a measure of how objectionable different start-ups are, and developing a scalable procedure using Amazon Mechanical Turk (AMT) to develop a multiple-rater assessment of the controversiality of a large number of ventures. Use of multiple raters for every start-up allows us to overcome the significant uncertainty in the individual assessments. The procedure’s relatively low cost allows it to be scaled effectively, thus allowing future research to consider much larger samples than we used here, potentially achieving close to full coverage of US start-up companies that have received venture capital funding over the last three decades.

All in all, we believe that the present study presents promising theoretical findings coupled with conceptual foundations and a scalable data collection procedure. We hope that future research will build upon these initial steps to answer a variety of questions regarding the role of legitimacy in determining the ability of companies to bring innovations to the market.
FIGURES AND TABLES

Table 1: Descriptive statistics of the factual (N=11,454) and counterfactual samples (N=114,540)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Whole sample</th>
<th>Factuals</th>
<th>Counterfactuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>Factual observation</td>
<td>0.09</td>
<td>0.29</td>
<td>1.00</td>
</tr>
<tr>
<td>Focal investor number of investments (logged)</td>
<td>2.40</td>
<td>1.35</td>
<td>2.85</td>
</tr>
<tr>
<td>Focal investor number of funds raised (logged)</td>
<td>0.65</td>
<td>0.54</td>
<td>0.79</td>
</tr>
<tr>
<td>Focal investor IPO rate</td>
<td>0.17</td>
<td>0.20</td>
<td>0.19</td>
</tr>
<tr>
<td>Focal investor eigenvector centrality</td>
<td>0.18</td>
<td>0.22</td>
<td>0.27</td>
</tr>
<tr>
<td>Distance between the focal investor and portfolio company (logged)</td>
<td>6.43</td>
<td>1.77</td>
<td>5.26</td>
</tr>
<tr>
<td>Industry specialization of the focal investor in focal industry</td>
<td>0.13</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>Average direct ties with other investors in syndicate (logged)</td>
<td>0.27</td>
<td>0.61</td>
<td>0.67</td>
</tr>
<tr>
<td>Average indirect ties with other investors in syndicate (logged)</td>
<td>1.37</td>
<td>1.47</td>
<td>1.84</td>
</tr>
<tr>
<td>Objection score</td>
<td>1.72</td>
<td>1.85</td>
<td>1.72</td>
</tr>
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</table>

Table 2: Correlation coefficients of the whole sample (N=125,994)

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<tr>
<th>Variables</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<td>1. Factual observation</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2. Focal investor number of investments (logged)</td>
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<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Focal investor number of funds raised (logged)</td>
<td>0.08</td>
<td>0.48</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>4. Focal investor IPO rate</td>
<td>0.03</td>
<td>0.26</td>
<td>0.11</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<td>5. Focal investor eigenvector centrality</td>
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<td>0.78</td>
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<td>0.27</td>
<td>1.00</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>6. Distance between the focal investor and portfolio company (logged)</td>
<td>-0.21</td>
<td>-0.06</td>
<td>-0.03</td>
<td>-0.01</td>
<td>-0.09</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>7. Industry specialization of the focal investor in focal industry</td>
<td>0.09</td>
<td>0.15</td>
<td>0.06</td>
<td>0.05</td>
<td>0.06</td>
<td>-0.05</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Average direct ties with other investors in syndicate (logged)</td>
<td>0.20</td>
<td>0.42</td>
<td>0.20</td>
<td>0.16</td>
<td>0.56</td>
<td>-0.12</td>
<td>0.07</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>9. Average indirect ties with other investors in syndicate (logged)</td>
<td>0.10</td>
<td>0.59</td>
<td>0.26</td>
<td>0.22</td>
<td>0.59</td>
<td>-0.08</td>
<td>0.10</td>
<td>0.68</td>
<td>1.00</td>
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<tr>
<td>10. Objection score</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.01</td>
<td>-0.04</td>
<td>-0.05</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.07</td>
<td>-0.07</td>
</tr>
</tbody>
</table>

Note: All correlations above 0.01 are significant at the p<0.05 level
Table 3: Conditional logit (grouped on the company investment round level) distinguishing realized from unrealized ties. Standard errors clustered by group. Two-tailed t-test values in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
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<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal investor number of investments (logged)</td>
<td>-0.0138</td>
<td>-0.0136</td>
<td>-0.0149</td>
<td>-0.0144</td>
<td>-0.0147</td>
<td>-0.0147</td>
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<tr>
<td></td>
<td>(-0.82)</td>
<td>(-0.80)</td>
<td>(-0.88)</td>
<td>(-0.86)</td>
<td>(-0.87)</td>
<td>(-0.87)</td>
</tr>
<tr>
<td>Focal investor number of funds raised (logged)</td>
<td>0.252*** 0.251*** 0.252*** 0.252*** 0.252*** 0.252***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.34)</td>
<td>(11.33)</td>
<td>(11.37)</td>
<td>(11.35)</td>
<td>(11.36)</td>
<td>(11.36)</td>
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<tr>
<td>Focal investor IPO rate</td>
<td>0.0698</td>
<td>0.0698</td>
<td>0.0701</td>
<td>0.07</td>
<td>0.0699</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(1.18)</td>
<td>(1.17)</td>
<td>(1.18)</td>
<td>(1.18)</td>
<td>(1.18)</td>
<td>(1.18)</td>
</tr>
<tr>
<td>Focal investor eigenvector centrality</td>
<td>-0.289** -0.289** 0.281** -0.287** -0.280** -0.281**</td>
<td></td>
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<tr>
<td></td>
<td>(-2.95)</td>
<td>(-2.94)</td>
<td>(-2.86)</td>
<td>(-2.93)</td>
<td>(-2.85)</td>
<td>(-2.86)</td>
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<tr>
<td>Distance between the focal investor and portfolio company (logged)</td>
<td>-0.324*** -0.309*** -0.324*** -0.324*** -0.309*** -0.300***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(-53.50)</td>
<td>(-37.20)</td>
<td>(-53.56)</td>
<td>(-53.51)</td>
<td>(-37.35)</td>
<td>(-37.41)</td>
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<td>Industry specialization of the focal investor in focal industry</td>
<td>1.405*** 1.406*** 1.407*** 1.406*** 1.408*** 1.408***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average direct ties with other investors in syndicate (logged)</td>
<td>1.216*** 1.217*** 1.150*** 1.210*** 1.144*** 1.151***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(42.96)</td>
<td>(43.01)</td>
<td>(34.68)</td>
<td>(43.05)</td>
<td>(31.19)</td>
<td>(34.8)</td>
</tr>
<tr>
<td>Average indirect ties with other investors in syndicate (logged)</td>
<td>-0.00487</td>
<td>-0.00513</td>
<td>-0.00692</td>
<td>-0.031</td>
<td>-0.00111</td>
<td>-0.00717</td>
</tr>
<tr>
<td></td>
<td>(-0.23)</td>
<td>(-0.25)</td>
<td>(-0.33)</td>
<td>(-1.31)</td>
<td>(-0.04)</td>
<td>(-0.35)</td>
</tr>
<tr>
<td>Objection score * Distance (logged)</td>
<td>-0.00850** -0.00850** -0.00850** -0.00845** -0.00850** -0.00850**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(-2.64)</td>
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<td>(-2.61)</td>
<td>(-2.60)</td>
<td>(-2.61)</td>
<td>(-2.60)</td>
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<tr>
<td>Objection score * Avg direct ties (logged)</td>
<td>0.0447*** 0.0490*** 0.0446***</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(3.77)</td>
<td>(3.17)</td>
<td>(3.74)</td>
<td></td>
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</tr>
<tr>
<td>Objection score * Avg indirect ties (logged)</td>
<td>0.0149* -0.00365</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>(2.26)</td>
<td>(-0.43)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations | 125994 | 125994 | 125994 | 125994 | 125994 | 125994 |
Pseudo R-square (%) | 19.15 | 19.17 | 19.18 | 19.16 | 19.20 | 19.20 |

Note: * p<0.05, ** p<0.01, *** p<0.001
Table 4: Fixed effects linear probability model (grouped on the company investment round level) distinguishing realized from unrealized ties. Standard errors clustered by group. Two-tailed t-test values in parentheses.

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<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal investor number of investments (logged)</td>
<td>-0.000160 (-0.13)</td>
<td>-0.000180 (-0.14)</td>
<td>-0.000285 (-0.22)</td>
<td>-0.000254 (-0.20)</td>
<td>-0.000288 (-0.23)</td>
<td>-0.000296 (-0.23)</td>
</tr>
<tr>
<td>Focal investor number of funds raised (logged)</td>
<td>0.0233*** (12.92)</td>
<td>0.0233*** (12.93)</td>
<td>0.0232*** (12.90)</td>
<td>0.0232*** (12.89)</td>
<td>0.0232*** (12.91)</td>
<td>0.0232*** (12.90)</td>
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<tr>
<td>Focal investor IPO rate</td>
<td>0.00273 (0.60)</td>
<td>0.00276 (0.61)</td>
<td>0.00284 (0.63)</td>
<td>0.00282 (0.62)</td>
<td>0.00285 (0.63)</td>
<td>0.00286 (0.63)</td>
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<td>Focal investor eigenvector centrality</td>
<td>-0.0241** (-3.17)</td>
<td>-0.0240** (-3.15)</td>
<td>-0.0233** (-3.07)</td>
<td>-0.0230** (-3.14)</td>
<td>-0.0233** (-3.06)</td>
<td>-0.0233** (-3.07)</td>
</tr>
<tr>
<td>Distance between the focal investor and portfolio company (logged)</td>
<td>-0.0333*** (-67.32)</td>
<td>-0.0313*** (-66.17)</td>
<td>-0.0333*** (-67.40)</td>
<td>-0.0333*** (-67.33)</td>
<td>-0.0316*** (-46.58)</td>
<td>-0.0317*** (-46.59)</td>
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<tr>
<td>Industry specialization of the focal investor in focal industry</td>
<td>0.126*** (26.50)</td>
<td>0.126*** (26.51)</td>
<td>0.126*** (26.53)</td>
<td>0.126*** (26.54)</td>
<td>0.126*** (26.54)</td>
<td>0.126*** (26.54)</td>
</tr>
<tr>
<td>Average direct ties with other investors in syndicate (logged)</td>
<td>0.140*** (63.05)</td>
<td>0.141*** (63.15)</td>
<td>0.141*** (50.22)</td>
<td>0.141*** (63.19)</td>
<td>0.131*** (45.42)</td>
<td>0.131*** (50.34)</td>
</tr>
<tr>
<td>Average indirect ties with other investors in syndicate (logged)</td>
<td>-0.00983*** (-6.89)</td>
<td>-0.00987*** (-6.91)</td>
<td>-0.0100*** (-7.01)</td>
<td>-0.0130*** (-8.04)</td>
<td>-0.00957*** (-5.59)</td>
<td>-0.0100*** (-7.03)</td>
</tr>
<tr>
<td>Objection score * Distance (logged)</td>
<td>-0.00116*** (-4.32)</td>
<td>-0.000961*** (-3.55)</td>
<td>-0.000958*** (-3.54)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Objection score * Avg direct ties (logged)</td>
<td>0.00709*** (7.31)</td>
<td>0.00708*** (5.74)</td>
<td>0.00671*** (6.88)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Objection score * Avg indirect ties (logged)</td>
<td>0.00189*** (4.18)</td>
<td>-0.000281 (-0.49)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.252*** (66.17)</td>
<td>0.252*** (66.17)</td>
<td>0.252*** (66.30)</td>
<td>0.252*** (66.24)</td>
<td>0.252*** (66.29)</td>
<td>0.252*** (66.30)</td>
</tr>
</tbody>
</table>

Observations: 125994
Pseudo R-square (%): 19.15

Note: * p<0.05, ** p<0.01, *** p<0.001
Table 5: Conditional logit (grouped on the company investment round level) distinguishing realized from unrealized ties. Standard errors clustered by group. Two-tailed t-test values in parentheses.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Seed only</td>
<td>Non-seed</td>
<td>All</td>
</tr>
<tr>
<td>VC firm number of investments (logged)</td>
<td>-0.0147</td>
<td>0.0299</td>
<td>-0.0275</td>
<td>-0.0164</td>
</tr>
<tr>
<td></td>
<td>(-0.87)</td>
<td>(0.72)</td>
<td>(-1.48)</td>
<td>(-0.97)</td>
</tr>
<tr>
<td>VC firm number of funds raised (logged)</td>
<td>0.252***</td>
<td>0.190***</td>
<td>0.264***</td>
<td>0.252***</td>
</tr>
<tr>
<td></td>
<td>(11.36)</td>
<td>(3.35)</td>
<td>(10.93)</td>
<td>(11.37)</td>
</tr>
<tr>
<td>VC firm IPO rate</td>
<td>0.07</td>
<td>-0.534**</td>
<td>0.169**</td>
<td>0.0714</td>
</tr>
<tr>
<td></td>
<td>(1.18)</td>
<td>(-3.15)</td>
<td>(2.67)</td>
<td>(1.20)</td>
</tr>
<tr>
<td>VC firm eigenvector centrality</td>
<td>-0.281**</td>
<td>-0.0821</td>
<td>-0.313**</td>
<td>-0.274**</td>
</tr>
<tr>
<td></td>
<td>(-2.86)</td>
<td>(-0.38)</td>
<td>(-2.80)</td>
<td>(-2.78)</td>
</tr>
<tr>
<td>Distance between VC firm and portfolio company (logged)</td>
<td>-0.309***</td>
<td>-0.335***</td>
<td>-0.303***</td>
<td>-0.303***</td>
</tr>
<tr>
<td></td>
<td>(-37.41)</td>
<td>(-17.20)</td>
<td>(-33.01)</td>
<td>(-33.04)</td>
</tr>
<tr>
<td>Industry specialization of the VC firm in focal industry</td>
<td>1.408***</td>
<td>1.695***</td>
<td>1.358***</td>
<td>1.408***</td>
</tr>
<tr>
<td></td>
<td>(28.28)</td>
<td>(13.24)</td>
<td>(25.15)</td>
<td>(28.30)</td>
</tr>
<tr>
<td>Average direct ties with other VCs in syndicate (logged)</td>
<td>1.151***</td>
<td>1.112***</td>
<td>1.168***</td>
<td>1.188***</td>
</tr>
<tr>
<td></td>
<td>(34.8)</td>
<td>(16.57)</td>
<td>(30.75)</td>
<td>(32.19)</td>
</tr>
<tr>
<td>Average indirect ties with other VCs in syndicate (logged)</td>
<td>-0.00717</td>
<td>-0.147**</td>
<td>0.0223</td>
<td>-0.00847</td>
</tr>
<tr>
<td></td>
<td>(-0.35)</td>
<td>(-3.11)</td>
<td>(0.96)</td>
<td>(-0.41)</td>
</tr>
<tr>
<td>Objection score * Distance (logged)</td>
<td>-0.00845**</td>
<td>-0.0258**</td>
<td>-0.00577</td>
<td>-0.00581</td>
</tr>
<tr>
<td></td>
<td>(-2.60)</td>
<td>(-3.08)</td>
<td>(-1.63)</td>
<td>(-1.64)</td>
</tr>
<tr>
<td>Objection score * Avg direct ties (logged)</td>
<td>0.0446***</td>
<td>0.0975***</td>
<td>0.0336*</td>
<td>0.0341*</td>
</tr>
<tr>
<td></td>
<td>(3.74)</td>
<td>(3.52)</td>
<td>(2.53)</td>
<td>(2.57)</td>
</tr>
<tr>
<td>Seed-stage * Distance (logged)</td>
<td>-0.0318</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.48)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seed-stage * Avg direct ties (logged)</td>
<td>-0.160*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.50)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seed-stage * Distance (logged) * Objection Score</td>
<td>-0.0199*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.18)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seed-stage * Avg direct ties (logged) * Objection Score</td>
<td>0.0626*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.04)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations                                               | 125994        | 22924         | 103070        | 125994        |
Pseudo R-square (%)                                         | 19.20         | 24.46         | 18.18         | 19.25         |

Note: * p<0.05, ** p<0.01, *** p<0.001
REFERENCES


APPENDIX – AMAZON MECHANICAL TURK DATA COLLECTION

Coders recruited through Amazon Mechanical Turk (AMT) were asked to read descriptions of start-up companies and then evaluate how objectionable these companies were likely to be. The assignment was organized in batches, where each batch included descriptions of five companies that a rater was then assigned. Each rater could choose to accept work on one or more batches (but no rater could evaluate the same company more than once). In return, the raters were paid a small amount of money to compensate them for their effort. We used a feature available through AMT that allows us to restrict respondents to individuals who are located in the U.S., so that all respondents are working within a frame of reference based on a single (although admittedly large and diverse) country.

For each company description, the rater was asked to rate how objectionable the company might be considered on a scale from one to five, with one being not objectionable at all and five being very objectionable. They had the option to respond that the description did not provide enough information for an accurate assessment. The following is a sample question:

Please read the following statement about the activities of a company:

*Develops an Internet marketplace for trading commercial debt. The Company breaks down the restrictive and inefficient structure of the secondary market while opening the door to whole loan sales and purchases regardless of organization or asset size.*

How likely is it that people will find the activities of this firm objectionable?

- Not objectionable
- Few people are likely to object
- Some people might object
- People are somewhat likely to object
- People are very likely to object
- Not enough information

Each list of questions had five questions of the same type so each rater would rate five company descriptions at a time. The questions were constructed by randomly sampling
companies from the main data set (out of 16,685 firms). Each list of questions was automatically assigned to five separate raters, giving five observations of the strength of objection for each company in the sample. Responses of “not objectionable” or “few people are likely to object” were assigned a score of zero; a response of “some people might object” received a score of one; “people are somewhat likely to object” received a score of two; and “people are very likely to object” received a score of three. We calculated the final score as the sum of the scores from each rater.

The motivation for framing the question as “How likely is it that people will find the activities of this firm objectionable?” rather than asking whether the respondents themselves would object, was to minimize the impact of the respondents’ personal views. In separate analysis intended to better understand the response patterns of the AMT respondents, we explored using a four-item survey, asking respondents to answer the question in terms of whether they themselves would find the activities of the firm objectionable, as well as whether “customers”, “investors”, and “people” would be likely to do so. Individual raters showed a high consistency across the four different questions (Cronbach’s alpha = .96), indicating that it was justified to use a single item scale in order to maximize the coverage of firms with the available resources. The inter-rater reliability, however, was somewhat higher when the question was framed in terms of “people” than for other phrases, indicating that respondents were able to evaluate general tendencies of the population regardless of their own views.

The final score for each firm was based on the combined score of five raters, further reducing the effect of any given individual’s bias. The inter-rater reliability measured as the intraclass correlation coefficient (ICC) with the combined score as the unit of analysis was moderate (ICC=.62), according to the guidelines discussed by Koo and Li (2016). Given that objectionability is an inherently subjective construct and the raters were not trained, it is not
unexpected that the inter-rater reliability is relatively low, but for the purposes of this research, we felt that it was adequate. We did not include a coding key or coding instructions beyond the question; a coding key would have had to be quite detailed, which would have increased the cost per observation significantly, and thus limited the number of observations we were able to gather. The specific setup was intended to maximize the number of observations while still requiring multiple raters for each observation, given the available resources.

Examples of company descriptions and ratings

The startup described above, at the start of this appendix, resulted in a rating of 5, which is in the middle of the range (but well above the mean, because the scores are mostly clustered around zero). For a company that lies at the upper end of the strength objection rating, one might consider the following description, which received a rating of 12 (which is at the upper end of the range):

*Develops intelligent computing applications. The company’s application detects people and moving objects in video. Its software offers video monitoring to anyone with a webcam or network camera.*

Here, the ability for anyone to set up video monitoring with minimal effort is likely what triggered the evaluation of this company to be viewed as objectionable by some. On its website, the company emphasizes the simplicity for individual users setting up unobtrusive video monitoring with minimal effort, which does raise privacy concerns. Another description, of an online gaming company, received a rating of 11:

*Develops Internet-based applications. The company's first product lets users buy and sell friends like commodities with virtual currency; the person's value increases each time he is bought.*

The company’s product is a social game and is of course not intended for the actual sale of humans, but the mechanics of the game are nevertheless set up in a way that many people
would find disturbing and objectionable. At the other end of the range are two descriptions that elicited scores of 0, the first one being in the used cardboard industry:

*Supplies used cardboard boxes. The Company acquires used boxes from businesses, then UCB certifies, brands, and resells the very same boxes to customers who move each year, as well as to small businesses that use boxes for shipping. The Company offers corrugated boxes, tapes, markets, bubble wrap, box cutters, and packing materials.*

And the other is in the air-conditioning business:

*Design, manufacture and install 'eutectic' cool storage systems which are used to shift air conditioning load from daytime on-peak hours to nighttime off-peak hours, thus reducing a building owner's air conditioning electric bill, and helping the electric utility companies balance their load.*

As these examples demonstrate, there is a considerable range in the potential for objections about start-ups’ business models. These firms have all received VC investments, so their descriptions will not have accounts of activities that are illegal or would obviously make the companies taboo for investors. They do, however, list characteristics that may lead some people to avoid affiliation with the companies.