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Evaluating Venture Technical Competence in Venture Capitalist Investment Decisions

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Although much research emphasizes the importance of venture technical competence for venture success and, therefore, the importance of venture technical competence in venture capitalist (VC) investment decisions, we know little about why some VCs may be better than others at assessing the technical competence of ventures. We gathered unique and proprietary data from 33 VCs and 308 ventures that sought Series A funding from those VCs. We show that VC assessment of ventures predicts VC investment, and venture technical competence predicts subsequent venture failure. This means that VCs that overassess ventures are more likely to invest in firms that are more likely to fail. We then show that higher VC technical competence leads to lower errors in assessment, but that greater similarity between the VC and venture in technical competence leads to higher assessments, ceteris paribus. We thus conclude that VC competence enhances the accuracy of VC assessments, but similarity in technical competence between VCs and ventures may lead to positive assessment bias.

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1. Introduction

> I don't know about Techstars, but we would have a hard time funding a startup without a strong technical founder. I'd go so far as to say that it is irresponsible to start a technology company without a technical founder. (Andreessen 2011)

> We reject teams for a variety of reasons, and lack of tech expertise is one of the big ones.... Imagine going on a transatlantic voyage without a ship. Without software engineering knowledge, we will fare no better. We need good IT knowledge to correctly judge a team's tech expertise.
> —A reputed venture capitalist in the IT domain

Since a venture's human capital has a significant impact on future growth and performance (Colombo and Grilli 2005, Cooper et al. 1994, Haber and Reichel 2007, Shrader and Siegel 2007), the ability of a venture capitalist (VC) to accurately evaluate the venture's human capital should have a strong impact on the quality of the VC's funding decision (Baum and Silverman 2004, Patzelt 2010). In the technology domain, one of the most important aspects of venture human capital is technical competence—i.e., a venture's ability to effectively address technology-related challenges such as programming, data access, data development, information technology (IT) architecture, and so forth (Lee et al. 1995, Trauth et al. 1993). The leading quotations above illustrate the clear preference of VCs for investing in technology ventures with strong technical competence.

Although technical competence may be an important predictor of technology-venture success and an important component of VC investment decisions, we know surprisingly little about the underlying abilities of VCs to evaluate the technical competence of ventures. As we shall see, research seems to have taken for granted that VCs are fully capable of evaluating the technical competence of venture teams when making investment decisions. If all VCs are equally able to evaluate the technical competence of technology ventures, then the lack of research should not be concerning. However, if VCs systematically vary in their abilities to evaluate the technical competence of ventures, then some VCs may be better situated to assess the likelihood of venture survival and performance. Similarly, VCs with poor abilities to assess venture technical competence may consistently invest in ventures with poor performance prospects. Accordingly, understanding why and how VCs evaluate the technical competence of technology ventures may help to explain performance differences among technology VCs.

We argue that VCs do vary in their abilities to assess the technical competence of venture teams and that two factors predicting that variance are the VC's own technical competence and the similarity in technical competence between the VC and venture. We thus ask two tightly coupled research questions: (1) Does VC technical competence improve assessment accuracy when evaluating the technical competence of ventures and the quality of subsequent investment decisions? And (2) does similarity in technical competence between VCs and ventures positively bias assessments and affect the quality of subsequent investment decisions? We leverage a unique and proprietary data set of 33 VCs and 308 ventures that those VCs considered for investment. The VCs and technology heads at the ventures both took validated quizzes to test their own technical competence, and, in addition, each VC evaluated the technical competence of each venture it considered. Our data are uniquely positioned to allow us to explore the effect of VC technical competence on accuracy when evaluating venture technical competence, the effect of similarity in technical competence on VC evaluations of venture competence, investment decisions and venture performance outcomes.

We thus contribute to the VC investment decision literature both theoretically and empirically. From a theory perspective, we first partially explain why some VCs may be better able to assess the technical competence of ventures than others and directly challenge the implicit assumption that VCs are similar in their abilities to evaluate venture technical competence. From an empirical perspective, we provide a unique empirical setting that allows us to observe VC technical competence, VC assessments of venture technical competence, actual venture technical competence, actual VC investment decisions, and real venture performance outcomes. Prior studies have lacked the data depth to explore all of these factors in the same models.

In the next section we establish the baseline expectations that (1) VC assessments of venture technical competence predict VC investments and (2) venture technical competence predicts the likelihood of venture failure. The clear implication of these expectations is that overassessing venture technical competence can lead to investing in ventures that may be more likely to fail. In §3 we then show that VC technical competence leads to lower error magnitudes when assessing ventures, and that greater similarity between VC and venture technical competence leads to higher assessments, ceteris paribus. Thus, increased VC technical competence increases assessment accuracy, but similarity between the VC and venture can lead to positive bias in assessments. We then describe our data and results and finally conclude with implications for future research.

2. Why Assessments Matter for VC Outcomes

A baseline expectation from prior VC investment research is that the probability of investment should increase with the VC's assessment of the venture's technical competence and that the likelihood of venture failure should decrease with increased actual technical competence. Before developing these expectations in detail, however, it is useful to clarify what we mean by technical competence and why technical competence is important in VC investment decisions.

As mentioned in the introduction, technical competence is a venture's ability to effectively address IT-related challenges such as programming, data access, data development, IT architecture, and so forth (Lee et al. 1995, Trauth et al. 1993). Both Marc Andreessen and the unnamed venture capitalist in the second introductory quotation consider carefully the technical expertise and competence of the ventures' key workers. Their emphasis on venture technical competence seems well founded in the academic literature (e.g., Baum and Silverman 2004, Zacharakis and Meyer 2000). Shepherd (1999), for example, finds that the industry expertise of the founding team is one of the most important factors in predicting venture survival. Similarly, a host of studies show that the industry expertise of a venture's key workers significantly predicts the future performance of the venture (Colombo and Grilli 2005, Crook et al. 2008, Haber and Reichel 2007, Shrader and Siegel 2007). Accordingly, if the venture seeks to grow and survive as a technology-intensive enterprise, then the technical competence of its key workers should be a critical predictor of its future success. Indeed, some scholars have shown that technical competence can be a source of sustained competitive advantage for the firm (Bharadwaj 2000, Mata et al. 1995, Pavlou and El Sawy 2006, Tambe et al. 2012, Tippins and Sohi 2003).

Although venture technical competence is important for venture performance (Colombo and Grilli 2005, Haber and Reichel 2007, Shrader and Siegel 2007) and VC decisions to invest (Baum and Silverman 2004, Zacharakis and Meyer 2000), it may be quite difficult for the VC to evaluate the technical competence of a venture, even when the venture opens its doors to the VC. The venture may project high levels of technical competence, even if its true competence is low. Entrepreneurs are notoriously overconfident, so they may believe that they are far more competent than they actually are (Busenitz and Barney 1997, Forbes 2005, Lowe and Ziedonis 2006). If they believe that they are highly competent, then they will project that competence to potential VCs, even if they are not. Also, VCs face a moral hazard problem when investing in ventures (Bergemann and Hege 1998, Wang and Zhou 2004). In other words, there is great uncertainty about the future success of the venture, and the venture has incentive to convince the VC that there is a high probability of future success even if the venture has private information to the contrary. Accordingly, the venture may try to project a high level of technical competence even if it does not have it, to secure funding. Thus, whether the venture is honest and overconfident or dishonest, the venture still may project a higher level of technical competence than it really has. It may be very difficult for the VC to cut through those projected signals to evaluate the true technical competence of the venture. In other words, there may be a gap between the venture's true technical competence and the VC's assessment of the venture's technical competence.

The fairly straightforward concern with the gap between VC assessments and actual venture competence is that the decision makers act on their perceptions of reality rather than on the unknown objective reality (March 1994). From the VC's perspective, the assessment is the best indicator of the true venture technical competence, and, therefore, investment decisions are likely based on the assessment. Accordingly, we should expect the probability of VC investment to increase with the VC's assessment of venture technical competence. Stated formally:

Hypothesis 1A (H1A). *The probability of VC investment increases as the VC's assessment of a venture's technical competence increases*, *ceteris paribus*.

Whereas the VC's assessment of venture technical competence may drive the VC's investment decisions, the actual venture technical competence is likely to drive venture performance outcomes. Based on the logic described above (e.g., Colombo and Grilli 2005, Kor 2003), higher venture technical competence likely leads to higher venture performance. In particular, higher venture technical competence likely leads to lower failure rates among new ventures because technically competent teams are better positioned to deal with the technical challenges required to successfully bring new products and services to market. Thus:

Hypothesis 1B (H1B). *The probability of venture failure decreases as the venture's technical competence increases*, *ceteris paribus*.

The hypotheses above may seem straightforward initially. Extant research on VC decision making certainly supports the logic that VCs will be more likely to invest in ventures that they believe are more competent and that ventures that are more competent are more likely to succeed. These hypotheses taken together, however, reveal an important implicit assumption in extant models. Specifically, prior models implicitly assume that VCs are similarly able to assess venture technical competence. Consider, for example, Colombo and Grilli's (2005) rich study exploring the impact of founding team human capital on the growth of new technology firms. Their theory and empirical design leverage founders' years of education, years of industry experience, managerial experience, and prior entrepreneurial experience as indicators of the competence of the founding team. Colombo and Grilli's (2005) approach is representative of other research on venture team competence and/or experience (e.g., Baum and Silverman 2004, Kor 2003, Zacharakis and Meyer 2000). The logic underlying the use of demographic experience variables is that that experience is the best observable proxy for true competence. Thus, if these easy-to-observe measures are the key competence indicators, then we should not expect variance in VCs' abilities to assess venture technical competence. VCs should be similarly able to assess venture teams.

But although data availability for demographic experience measures has made such measures standard in VC decision making and venture performance studies, even the scholars using these indicators recognize the potential limitations of using experience to proxy for competence (e.g., Kor 2003). Competence does not necessarily follow experience, and experience is not necessarily required for competence. *BusinessWeek*'s annual survey of young tech entrepreneurs, for example, illustrates many highly successful and competent tech founders who lacked experience at the time of founding. Accordingly, when it comes to actual investment decisions, VCs may be more likely to rely on their own subjective assessments of venture technical competence than the objective measures of experience typically invoked in prior research. Our qualitative conversations with VCs in the research process seem to support this notion. If these subjective assessments are important, then explaining why some VCs have superior assessment abilities is critical for improving models of VC decision making and subsequent outcomes. Constructing such a model is the primary purpose of the next section.

3. Predicting VC Assessments of Venture Technical Competence

3.1. VC Technical Competence Increases Assessment Accuracy

Theories of expert knowledge suggest that VCs with higher technical competence should be better able to accurately assess the technical competence of ventures (Castanias and Helfat 2001, Eisenhardt and Schoonhoven 1990, Kor 2003, Shepherd et al. 2003). Research supports that highly competent individuals in a specific domain are better able to discern nuances within that domain. Historical research on chess experts shows that these experts have deeper understanding of the game, but also have greater recall related to the game (Chase and Simon 1973). Their more advanced cognitive structures related to the many different problems and possibilities in chess help them to more quickly diagnose a specific chess situation. Accordingly, experts are better able to quickly evaluate situations in their domains because of their deep technical knowledge and experience (Gladwell 2007, Sternberg and Grigorenko 2003).

For the reasons mentioned above, deep context-specific knowledge is particularly valuable in the business domain where firms may need to quickly evaluate shifting external environments and make decisions accordingly. Kor (2003) finds that management competence in specific domains enhances the rate of entrepreneurial growth. She argues that this is because competent management teams are better able to synthesize the nuances in their situations and contexts and make appropriate decisions. Other research also supports the positive relationship between domain-specific managerial competence and venture performance (e.g., Castanias and Helfat 2001, Eisenhardt and Schoonhoven 1990).

The same principles underlying theories of expert knowledge also likely apply in the context of VCs investing in technology ventures (Shepherd et al. 2003). Specifically, as a VC's technical competence increases, that VC should be better able to observe the nuances in venture technical knowledge and, therefore, determine the extent to which the venture also has technical competence. Highly competent VCs should know what questions to ask to validate the technical claims made by ventures, and they should be better able to recognize any technical constraints or difficulties the venture may face moving forward. These VCs can comprehend any technical uncertainties and complexities and they can carefully evaluate how ventures respond to their various questions. This is emphasized in the second leading quotation of the article when the VC mentions that he needs technical knowledge to assess the technical competence of a venture's human capital. Thus, VCs with high levels of technical competence both know what questions to ask as well as how to evaluate the quality of the answers they receive.

The value of VC technical competence can be illustrated by a hypothetical example based on rich interviews conducted by one of the authors. A particular venture with a low level of technical competence (lo-venture, for short) pitches its business model to both a VC with high technical competence (hi-VC, for short) and a VC with low technical competence (lo-VC, for short). One major challenge for the venture is the need to quickly scale up operations in the face of an exponential increase in traffic load. Both VCs ask the venture about how to deal with this challenge, and the venture replies that they will move their application to the distributed environment of Amazon Web Services when necessary. The lo-VC is satisfied with this response, but the hi-VC follows up with additional questions such as whether the application is built around a shared database, what kind of abstraction they have created to scale the catching layer, what they have done to make their process asynchronous, and so forth. The venture is still struggling to get the application running on a single server system and, therefore, does not have satisfactory answers to the hi-VC's questions. Accordingly, the hi-VC is far better prepared to determine the true technical competence of the venture.

Thus, we expect VCs with high technical competence to be more accurate in their assessments of venture technical competence. Formally:

Hypothesis 2 (H2). *VCs with higher technical competence will have lower error magnitudes when assessing the technical competence of ventures.*

3.2. Similarity in VC and Venture Technical Competence Leads to Positive Assessment Bias

Whereas the accuracy of VC assessments may increase with VC technical competence, accuracy may decrease with greater similarity between VCs and ventures. Franke et al. (2006) apply this similarity logic to the VC context and show that VCs evaluate venture teams more positively when they have similar training and professional experience. Although we do not dispute their findings, we also note that their study has at least two important limitations. First, like most similarity bias research, their work focuses on easy-to-observe demographic similarities between VCs and venture teams. Second, their research explores ex ante evaluations that do not involve social interactions between the VCs and the venture teams.

One of the key findings in social judgments research is that assessments of others are reciprocally updated over time and through interactions (Klimoski and Donahue 2001). In other words, evaluators make initial evaluations that they then update as they receive additional relevant information. With this reciprocal updating process in mind, it is important to note that the VC investment decision process occurs through multiple interactions between the VCs and the ventures. For simplification purposes, we can consider at least two important stages, namely, prescreening potential ventures for presentations and selecting ventures for investments from among those invited to give presentations.

Prior similarity bias research in the VC context has explained such bias for the prescreening stage, but not for the investment decision stage. Franke et al. (2006) use a creative conjoint method that effectively reveals VC preferences based on different scenarios. Their work provides high-level demographic information about venture teams and then observes VC preferences for venture teams based on demographic similarities. Their approach seems to match the real process of VC prescreening well; i.e., VCs have access to business plans and high-level demographic information about venture teams before deciding whether or not to invite them to give presentations.

Using demographic similarity as a signal of underlying competence may occur at the prescreening level, but these demographic factors may be too high level to be useful during the investment decision stage when VCs and ventures interact, and, therefore, when VCs have greater opportunities to personally evaluate competence. Once the VC and the venture team start interacting in the intense presentation environment, the VC can ask detailed and probing questions to determine the extent to which the venture team possesses the desired competence. In the face of these more detailed interactions, the demographic characteristics may become less important in the social judgments of the VC, and the social experience may become more important (London 2001).

We argue that in situations where the social experience is important for social judgments, the similarity in actual technical competence may explain positive bias in competency assessments. The logic for our theory comes from foundational work in organizational theory suggesting that the frequency and positivity of interpersonal interactions between two actors increases with the ease of communication between those two actors (March and Simon 1958). As Zenger and Lawrence (1989) review and discuss in detail, the ease of communication between two actors increases when they have common vocabularies and common interpretations of environmental stimuli—i.e., a shared language. They argue that shared language between individuals "reflects similarities in how they interpret, understand, and respond to information" (Zenger and Lawrence 1989, p. 355). Thus, two individuals with a shared language prior to an initial social interaction are more likely to connect and understand each other (Murnieks et al. 2011). They are more likely to interpret situations and approach problems in similar ways. Ultimately, coordination and communication will be much easier between two people with a shared language, ceteris paribus (Katz and Kahn 1966, March and Simon 1958). When communication and coordination increase, then the positive energy in interactions increases (Quinn and Dutton 2005), and that positive energy increases the positive affect within relationships (Quinn 2007). As the positive affect within relationships increases, individuals are more likely to assess each other positively in all dimensions, including intelligence and competence (Nathan and Lord 1983, Nisbett and Wilson 1977, Tsui and Barry 1986).

Technical competence can be a shared language between VCs and ventures when their levels of technical competence are similar. As an individual's technical competence increases, the complexity of that individual's mental models and schemas for addressing technical challenges increases (Johnson-Laird 1983). This increased complexity makes it easier for the individual to diagnose technical problems and identify creative solutions to those problems. Thus, two people with similar levels of technical competence likely have similar levels of complexity in their mental models and schemas. As they begin to communicate with each other, they are likely to find that this common level of competency allows them to communicate more quickly and easily with one another. Each party finds that the other quickly and readily understands technical comments and ideas at similar levels without a need for detailed explanation and discussion (Biernat et al. 1997).

Applying this logic to the VC context, then, when VCs and venture teams have similar levels of technical competence, they are more likely to communicate effectively, efficiently and smoothly through the shared language of technical competence. Accordingly, the VC is more likely to experience positive affect in the interpersonal interactions with the venture team, and this positive affect is likely to lead to positive evaluations of the venture's skills, abilities, and performance potential. We thus expect that VCs will rate ventures higher on technical competence when VCs and ventures are more similar in technical competence. Formally:

Hypothesis 3 (H3). *The more similar the venture is to the VC in technical competence, the greater the VC's assessment of the venture's technical competence.*

An interesting consequence of Hypothesis 3 is that it contradicts the statistical regression to the mean phenomenon. Consider a rating scale of very low, low, average, high, and very high technical competence, and a case of a hi-VC evaluating a hi-venture. Regression to the mean suggests that the hi-VC should err on the side of underassessing the hi-venture, because in Hypothesis 3 we argued that when VCs and venture teams have similar levels of technical competence, they are likely to assess ventures' technical competence to be high. We thus expect that the hi-VC should evaluate the hi-venture as having high or very high technical competence. This scenario of hypothesis is theoretically interesting because it contradicts the statistical expectation from regression to the mean.

4. Data

The ideal test of our theory requires data on the actual technical competence of VCs, the actual technical competence of ventures, and the VCs' perceptions of the ventures' technical competence along with investment choices, subsequent performance outcomes, and a host of control variables. Since such a database does not exist in a secondary source, we approached VCs and ventures directly to collect the data for our study.

We began by identifying a random sample of 200 VCs that invest in early-stage IT ventures from the VentureXpert database. Of these 200, 47 VCs chose to participate in our study, for a 23.5% participation rate. As part of their participation, they completed an instrument to evaluate their technical competence. We statistically compared the VCs who chose to participate with those that did not using unpaired two-sample t-tests on the dimensions of VC age and fund size, two of the variables available to us for all VCs in the original sample. Our tests failed to reject the null hypothesis that the groups have similar average ages (p-value $= 0.26$, t-statistic $= 1.14$) and similar average fund sizes (p-value $= 0.24$, t-statistic $= -1.18$). Accordingly, we find no evidence to suggest that participating VCs are systematically different from the nonparticipating VCs in any observable way that may threaten the validity of our findings.

Of the 47 VCs who chose to participate in our initial data collection, 33 chose to participate further by providing information about the ventures that they invited to give presentations in the year 2008. To control for funding stage through sample selection, we only asked for ventures that were seeking Series A funding requests. The VCs invited 689 such ventures for presentations in 2008.[1] Since some VCs invited the same ventures, these 689 total invitations represented 530 unique ventures. The VCs subsequently offered 215 ventures term sheets for funding. The average fund size of the VCs was \$122.02 million, and the average valuation that the VCs offered ventures was \$14.67 million. The VCs completed an instrument for each venture that included the VC's assessment of the venture's technical competence. We statistically compared the 33 VCs who chose to participate further by providing venture information with the 14 that did not. We conducted unpaired two-sample t-tests on the dimensions of VC age, fund size, and technical competence. Both groups have a similar mean age (p-value $= 0.92$, t-statistic $= 0.0966$), similar fund size (p-value $= 0.2687$, t-statistic $= -1.199$), and similar technical competence (p-value $= 0.6566$, t-statistic $= 0.4476$). We find no evidence to suggest that the VCs who chose to participate further are systematically different from the VCs who chose not to participate further in any observable way that may threaten the validity of our findings.

We approached all 530 unique ventures that the 33 VCs invited to give presentations in 2008 and requested that their technology heads participate in our study. Out of these, 308 technology heads chose to participate in the first quarter of 2009. These ventures completed an instrument that measured the actual technical competence of the technology heads. We statistically compared the 308 ventures who chose to participate with the 222 that chose not to participate. Both groups have similar mean values for the amount of funding raised (p-value $= 0.27$, t-statistic $= 1.103$), founder reputation (p-value $= 0.71$, t-statistic $= -0.3680$), and founder experience (p-value $= 0.86$, t-statistic $= 0.3896$). We find no evidence to suggest that the ventures that chose to participate are systematically different from the ventures who chose not to participate in our study in any observable way that may threaten the validity of our findings. The participating ventures received a total of 396 invitations from VCs and 123 funding term sheets.

4.1. Key Variables

4.1.1. Technical Competence. Following best practices in the organizational literature on individual competence measurement (Ehrlinger et al. 2008, Kruger and Dunning 1999), we used an objective quiz to evaluate the technical competence of VCs and ventures. The VC responsible[2] for deciding whether or not to invest in a technology venture took the quiz

[1] It is possible that the ventures invited for presentations may be a biased sample because VCs may preselect ventures that are already similar to them. We do not believe this is a problem here for two reasons: (1) the data show significant variance in how similar VCs are to the ventures they are , and (2) a sample of ventures that are already similar to the VCs who select them would bias us against finding any results—even if the sample is biased, then it should strengthen the validity of our findings.

[2] We focus on the individual VC and not the VC firm for at least two reasons: (1) none of our VCs reported that interactions with their VC team changed their investment recommendations other than rare instances when they overlooked key information, and (2) our interviews with the VCs suggest that they do their due diligence on their own and then bring their fully formed recommendations back to their partners and teams.

to determine VC technical competence. The technology head[3] for each venture took the quiz to determine venture technical competence. This quiz was created through in-depth interviews with the chief technology officers (CTOs) of 11 IT and software companies. These CTOs used this quiz as one of their hiring exams for a total of 57 software professionals as a pretest. Based on this testing, the quiz was improved to make it clearer and more robust. The CTOs agreed that the quiz provides a reliable measure of an individual's technical competence. Accordingly, the number of correct answers on the quiz provides a numerical indicator of the technical competence of the person taking the quiz.[4]

To validate the quiz for the present research, we partnered with an IT venture that was actively recruiting recent IT graduates from universities. This venture was growing quickly and finding it difficult to divert its resources toward hiring. They agreed to use the quiz to test candidates on their technical competence and provided the grade point averages (GPAs) of all applicants who took the quiz. Ninety-eight graduating job candidates took the quiz. For these 98 job candidates, we found a positive and significant correlation between GPA and quiz score ($\rho = 0.81$, p-value < 0.000). Of the 98 candidates, 63 did not have any prior work experience, whereas the rest had one to three years of prior work experience. The correlation for these 63 candidates was $\rho = 0.86$ with $p < 0.000$, and the correlation for the remaining 35 candidates was $\rho = 0.78$ with $p < 0.000$. These high and statistically significant correlations between GPA and quiz score provide a strong independent test of the validity of the quiz for assessing technical competence.

In addition to testing the quiz with job candidates as described above, we also asked participating ventures and VCs to rate how effectively this quiz measured technical competence on a Likert-type scale of 1 to 5. These survey results strongly suggest that the quiz effectively measures technical competence. A histogram showing these responses is included in Figure EC.1 in the e-companion (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2014.2117).

[3] One concern raised in the review process is whether the technology head may have delegated the completion of the quiz. We do not think this is a concern for at least two reasons: (1) there were no incentives to participate, so it would be easier to not participate than to delegate if the head did not want to fill out the quiz; and (2) even if delegation did occur, it would likely bias the score upward because of social desirability bias; i.e., the technology head would delegate to someone equally or more competent than him- or herself.

[4] Although we cannot share the actual instrument in publication because of its proprietary nature, we made the instrument accessible to the editors and reviewers during the peer review process.

To test the consistency of the measurement of technical competence using quiz scores, we used the split-half method (Bollen 1989). In this method, a quiz is first divided into two parts, and the correlation between the quiz score of the two halves is calculated. The Spearman–Brown Prophecy formula is then applied to the correlation to calculate the reliability of the full quiz, which is given by $2 * \rho/(1 + \rho)$, where ρ is the correlation between the quiz scores of the two halves. The split-half reliability for our quiz is 0.887, which is substantially higher than the threshold value of 0.7 (Bollen 1989) and indicates that the quiz is reliable. We also replicated our analyses using scores from quiz halves. Results from these split halves were qualitatively similar to the results from the total score.

4.1.2. Assessment. Assessment is operationalized as the VC's assessment of venture technical competence. The VC's assessment of venture technical competence was obtained after each VC took the quiz. After taking the quiz, the VC answered the question, "how many questions (out of 40) do you think the technology heads of the following ventures would answer correctly?"

4.1.3. Assessment Error Magnitude. The VC's assessment error magnitude is calculated as the absolute value of the difference between the VC's assessment of venture technical competence and actual venture technical competence. Accordingly, the error magnitude is the absolute value of the difference between the VC's estimate of the technology head's quiz score and the actual quiz score for that technology head.

4.1.4. Dissimilarity. The hypothesis development focuses on similarity in technical competence between the VC and the venture, but we empirically use a measure of dissimilarity to aid interpretation. Dissimilarity is the absolute value of the difference between actual VC technical competence and actual venture technical competence. Accordingly, larger differences represent greater dissimilarity between the VC and the venture.

4.1.5. Investment Decision. *Investment decision* is a dummy variable coded 1 if the VC chose to offer a term sheet to the venture. This indicates that the VC saw enough promise in the venture to offer funding.

4.1.6. Venture Failure. *Venture failure* is a dummy variable coded 1 if a venture failed. We considered ventures as failed if they filed for bankruptcy or they ceased their operations during the three year window following 2008. Although it is possible that VCs may recover their investments by selling off ventures' assets even if ventures cease to operate, in our sample, none of the VCs were fortunate enough to recoup their investments by liquidating ventures' assets.

4.2. Control Variables

Prior research suggests at least four different categories of factors that likely affect VC funding decisions: aspects of the venture's environment, characteristics of the venture, characteristics of the VC, and characteristics of the VC–venture dyad (Baum and Silverman 2004; Franke et al. 2006, 2008; Zacharakis and Meyer 2000).

4.2.1. Environment Controls. VC assessments and funding decisions may differ by *industry category*. All firms in our sample come from the Software and Services category of the Venture Economics Primary Industry Minor Group classification of industries. This category has two subcategories: software and IT services. To control for different industry subcategories, we coded a dummy variable with a value of 1 if the firm was in the software subcategory and a value of 0 if the firm was in the IT services subcategory. Our data do not allow finer-grained measures of industry, but all companies fall strictly into one or the other subgroup. None of these firms include hardware- or equipment-related categories.

The amount of competition for VCs when choosing to invest in a venture may also influence VC assessments and subsequent decisions. The level of competition may raise the bar on the VCs' expectations for venture technical competence and may also affect the VCs' willingness to invest. To control for *potential competition* that VCs faced, we used the number of VCs that were interested in a venture. The VCs provided the number of VCs interested in each venture.

4.2.2. Venture Characteristics. Macmillan et al. (1985) investigated important criteria used by VCs to make funding decisions. Their findings helped us identify controls related to the characteristics of the founders such as founders' experience, founders' reputation, and founders' communication skills. *Founders' reputation* was operationalized by the average number of successful exits (initial public offerings and acquisitions) led by the founders of a venture. *Founders' industry experience* was measured by the average industry experience (in years) of the founders of a venture. *Founding team project management experience* was the average years of managing projects of the founding team. *Venture team size* was measured as the total number of team members on the venture team.

Hall and Hofer (1993) also examined VC decision making in a similar vein and indicated that, in addition to the above characteristics, factors related to the venture's financial situation such as amount raised, amount requested, and revenue can also influence VCs' decision making. *Amount of funding raised* was the actual amount of funding the venture received prior to the VC funding request. *Amount of funding requested* was the amount of funding the venture was requesting from the VC. *Projected revenue* was operationalized as a venture's assessment of its revenue in three years.

Prior literature indicates that the following additional venture characteristics can also influence VCs' decision making—venture age, venture size, and number of patents (MacMillan et al. 1985, Tyebjee and Bruno 1984). *Venture age* was measured as the difference in months between the date when the venture was incorporated and the date when the funding request was made. *Venture size* was measured as the 2008 U.S. market value of the business in dollars. *Number of patents* was measured by the count of patents a venture had applied for at the United States Patent Office.

4.2.3. VC Characteristics. *VCs' IT experience* was calculated as the number of years of experience the VCs had in the IT industry. The *VCs' overall experience* was operationalized as the total number of years of experience as a VC. *Total investments* were measured as the total number of investments that VCs made. *VCs' successes* was measured as the number of successful exits for the ventures that they funded (Shane and Stuart 2002, Tyebjee and Bruno 1984). *VCs' failures* were defined as the number of defaulted ventures that they funded. We considered a company as defaulted if it had filed for bankruptcy or had ceased its operations. The *fund size* was operationalized as total funds raised by VCs. It is also possible that VC ethnicity may affect decisions. Accordingly, *VC ethnicity* was coded using a dummy variable for Asian and a dummy variable for Hispanic. Both variables took a value of 1 if the VC was that ethnicity, or a value of 0 if the VC was Caucasian. *VC age* was measured in years.

4.2.4. VC–Venture Dyad Characteristics. Since dyad-specific factors may also affect VC investment decisions and subsequent outcomes, we controlled for the extent to which the venture comes to the VC through a trusted referral (Shepherd 1999). *Trusted referral* was measured if the venture was recommended to the VC from one of its trusted affiliates. This was coded using a dummy variable with a value of 1 if the venture came through a trusted referral and 0 otherwise. We also controlled for VCs' assessment of ventures' communication skills and management capability. *Communication* was measured as the VC's assessment of the venture technology head's communication skills on a Likert-type scale from 1 to 10 with higher scores representing better communication skills. *Management capability* was similarly measured as the VC's assessment of the managerial capabilities of the founding team on a Likert-type scale from 1 to 10, with higher scores representing better management skills.

Table 1 Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
Funding received	0.31	0.46	0	1
Venture failure	0.57	0.50	0	1
Assessment error magnitude	6.76	5.08	0	26
Assessment (out of 40)	23.79	6.50	4	40
Dissimilarity	8.06	5.56	0	26
VCs' technical competence (out of 40)	18.83	4.82	10	28
Ventures' technical competence (out of 40)	23.76	7.14	10	36
Dummy reference	0.32	0.47	0	1
Number of patents	1.22	2.22	0	10
Team size	2.78	1.31	1	6
Market size ($ billion)	6.77	3.71	0.04	17.74
Competition	1.95	1.91	0	7
Founder reputation	2.27	0.92	0	4
Founder experience (years)	8.50	2.78	1	16
Age of a venture (months)	13.11	1.75	8	18
Projected revenue ($ million)	5.30	1.10	2.32	8.69
Dummy software	0.37	0.48	0	1
Amount raised ($ 10^3)	476.62	197.30	100.45	930.49
Amount requested ($ million)	4.34	1.15	1.50	7.61
Project management experience (years)	3.39	1.48	0	8
Communication (scale of 1–10)	5.59	2.91	1	10
Management capability	3.94	1.32	1	10
VCs' failures	8.38	3.39	2	15
VCs' successes	2.58	1.44	1	6
Fund size ($ million)	129.11	70.02	36	245
VCs' experience (years)	7.95	2.73	5	16
Total investments	16.08	3.84	5	24
VCs' IT experience (years)	16.93	4.27	10	25
Dummy Asian VC	0.36	0.48	0	1
Dummy Hispanic VC	0.04	0.18	0	1
VC age	45.51	4.68	38	53

Descriptive statistics for all variables are provided in Table 1, and a correlation matrix is reported in Table EC.2 in the e-companion.

5. Empirical Analysis

5.1. Model for Predicting VC Investment Based on VC Assessment

Hypothesis 1A predicts that the probability of VC investment increases as the VC's assessment of venture technical competence increases. We used a logit random effects (RE) model to examine the probability that a VC will invest in a venture as a function of the VC's assessment and control variables. It is plausible that VC and venture unobserved effects might also influence VCs' investment decisions. Therefore, we account for potential unobserved effects with the random effects model.

The general specification of our model is $P(Invest_{ij} = 1 \mid Assess_{ij}, X_{ij}, \mu_i, \delta_j) = F(Assess_{ij}\alpha + X_{ij}\beta + \mu_i + \delta_j)$, where $P(Invest_{ij} = 1 \mid Assess_{ij}, X_{ij}, \mu_i, \delta_j)$ refers to the probability that a VC i will invest in a venture j for the given data, $F(\cdot)$ is the logit function, $Assess_{ij}$ is the assessment of VC i of technical competence of venture j, X_{ij} is a vector of exogenous variables comprising controls, μ_i captures the unobserved effects for a VC i, and δ_j captures the unobserved effects for the venture j. The results are shown as Model 1 in Table 2. As predicted, the coefficient on the assessment is positive and significant, providing strong support for Hypothesis 1A.

5.2. Model for Predicting the Probability of Venture Failure Based on VC Overassessment

Hypothesis 1B predicts that the probability of venture failure decreases as the technical competence of the venture increases. Just as above, we use a logit random effects model (that accounts for both VC and venture unobserved effects) to examine the probability of venture failure as a function of venture technical competence and control variables.

The general specification of the model is $P(Fail_j = 1 \mid Ventcomp_j, X_{ij}, \mu_i, \delta_j) = F(Ventcomp_j\alpha + X_{ij}\beta + \mu_i + \delta_j)$, where $P(Fail_j = 1 \mid Ventcomp_j, X_{ij}, \mu_i, \delta_j)$ refers to the probability of failure of a venture j, $F(\cdot)$ is the logit function, $Ventcomp_{ij}$ is the technical competence of venture j, X_{ij} is a vector of exogenous variables comprising controls, μ_i captures the unobserved effects for a VC i, and δ_j captures the unobserved effects for the venture j.

The results are shown in Model 2 in Table 2. As predicted, the extent of venture technical competence negatively and significantly correlates with subsequent venture failure, providing strong support for Hypothesis 1B.

5.3. Model for Predicting VC Assessment Error Magnitudes Based on VC Technical Competence

Hypothesis 2 predicts that VCs with higher technical competence will have lower error magnitudes. We use a random effects model (that accounts for both VC and venture unobserved effects) to examine the influence of VC technical competence on assessment error magnitudes.

The general specification of the model is $ErrAssVen_{ij} = VCComp_i\alpha + Z_{ij}\beta + \mu_i + \delta_j + \varepsilon_{ij}$, where $ErrAssVen_{ij}$ is the magnitude of assessment error of a VC i for a venture j, $VCComp_i$ is the technical competence of VC i, Z_{ij} is a vector of exogenous variables comprising controls, ε_{ij} is an idiosyncratic error, μ_i captures the unobserved effects for a VC i, and δ_j captures the unobserved effects for the venture j.

The results are shown in Model 3 in Table 2. As predicted, the coefficient on VC technical competence is negative and significant, suggesting that the higher the VC technical competence, the lower the VC's error magnitudes when assessing the technical competence of the venture. These results suggest strong support for Hypothesis 2.

Table 2 Analyses for Hypotheses Testing

	Model 1 (for H1A)	Model 2 (for H1B)	Model 3 (for H2)	Model 4 (for H3)
	Dependent variables			
	Funding received	*Venture failure*	*Absolute error in assessing ventures' technical competence*	*Assessment*
	All observations	Only those ventures that were funded	All observations	All observations
Assessment	0.1838*** (0.0448)			
Ventures' technical competence		−0.3825*** (0.0895)	−0.0324 (0.0365)	0.3995*** (0.0554)
VCs' technical competence	−0.012 (0.0377)	0.0599 (0.0716)	−0.6246*** (0.0360)	−0.3317*** (0.0495)
Dissimilarity				−0.5707*** (0.0675)
Dummy reference	1.1276*** (0.3317)	−0.2719 (0.5977)	1.1228*** (0.3441)	0.3178 (0.3925)
Number of patents	0.1812** (0.0716)	0.071 (0.1303)	0.0449 (0.0881)	0.2269*** (0.0834)
Venture team size	0.303** (0.1415)	0.2685 (0.3706)	−0.0555 (0.1640)	0.4797*** (0.1442)
Market size	0.1302*** (0.0488)	−0.2082** (0.1001)	0.0161 (0.0566)	0.0517 (0.0452)
Competition	0.1059 (0.0883)	0.2486 (0.2125)	0.0368 (0.1147)	0.0467 (0.1008)
Founder reputation	−0.0696 (0.1839)	0.2253 (0.5719)	−0.0998 (0.2337)	−0.1113 (0.2259)
Founder experience	−0.0392 (0.0721)	−0.2867** (0.1358)	−0.0044 (0.0811)	−0.0025 (0.0860)
Age of a venture	0.0128 (0.1036)	0.1621 (0.2573)	−0.1443 (0.1128)	−0.0988 (0.1146)
Revenue	−0.0423 (0.1775)	0.1706 (0.3787)	0.068 (0.2072)	0.0025 (0.2114)
Dummy software	−0.4216 (0.3101)	0.394 (0.9777)	−0.2639 (0.3966)	−0.1802 (0.4144)
Amount raised	0.002* (0.0011)	−0.0006 (0.0022)	−0.0005 (0.0010)	0.001 (0.0013)
Amount requested	0.1564 (0.1765)	0.1999 (0.3520)	0.6861*** (0.2065)	0.0312 (0.1546)
Project management experience	0.0413 (0.1431)	0.7641 (0.1976)	−0.0487 (0.1686)	2.1638*** (0.2023)
Communication	−0.0361 (0.0563)	−0.1125 (0.0962)	0.2197** (0.0910)	0.159* (0.0842)
Management capability	0.2729* (0.1435)	0.2538 (0.1701)	0.2803* (0.1482)	0.4146*** (0.1579)
VCs' failures	−0.0902** (0.0422)	0.2832** (0.1373)	−0.045 (0.0505)	−0.0796 (0.0634)
VCs' successes	0.4683*** (0.1143)	−0.251 (0.3496)	0.125 (0.1104)	0.0308 (0.1395)
Fund size	−0.0023 (0.0019)	−0.0081** (0.0041)	−0.0012 (0.0018)	−0.0033* (0.0019)
VCs' experience	0.0558* (0.0316)	0.1131 (0.1585)	0.0755* (0.0446)	0.1041** (0.0468)
Total investments	−0.0389 (0.0418)	−0.0693 (0.0623)	0.0259 (0.0470)	0.0352 (0.0436)
VCs' IT experience	−0.0105 (0.0293)	−0.1483 (0.0922)	−0.015 (0.0290)	−0.0677* (0.0353)

Table 2 (Continued)

	Model 1 (for H1A)	Model 2 (for H1B)	Model 3 (for H2)	Model 4 (for H3)
	Dependent variables			
	Funding received	*Venture failure*	*Absolute error in assessing ventures' technical competence*	*Assessment*
	All observations	Only those ventures that were funded	All observations	All observations
Dummy Asian VC	0.0725	0.5301	0.5489**	0.1402
	(0.2622)	(0.5360)	(0.2799)	(0.3154)
Dummy Hispanic VC	0.2968	−1.5564	−0.2247	−1.7028***
	(0.4263)	(1.5700)	(0.4603)	(0.5321)
VC age	−0.0239	0.114	−0.0408**	−0.0296
	(0.0290)	(0.0759)	(0.0193)	(0.0369)
Constant	−8.6958***	−0.5792	16.9357***	16.2812***
	(2.4544)	(5.0957)	(2.8504)	(3.0674)
Log likelihood	−158.4443	−39.6523	−1,101.7523	−1,089.2725
N	396	120	396	396

Notes. VC and venture random effects are used in all of the models. In Model 1, ventures' technical competence is not included to see the independent effect of assessment on funding received. We thank an anonymous reviewer for suggesting this. It should be noted that including ventures' technical competence in Model 1 does not change coefficients substantially. Including dissimilarity in Models 1, 2, and 3 also does not change the results. Robust standard errors are in parentheses.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

5.4. Model for Predicting VC Assessment Based on Dissimilarity

Hypothesis 3 predicts that greater similarity (dissimilarity) between the VC technical competence and the venture technical competence leads to higher (lower) assessment of venture technical competence.

The general specification of the model is $Assess_{ij} = Dissim_{ij}\alpha + X_{ij}\beta + \mu_i + \delta_j + \varepsilon_{ij}$, where $Assess_{ij}$ is assessment of VC i of the technical competence of venture j, $Dissim_{ij}$ is the dissimilarity between technical competence of VC i and venture j, X_{ij} is a vector of exogenous variables comprising controls, ε_{ij} is an idiosyncratic error, μ_i captures the unobserved effects for a VC i, and δ_j captures the unobserved effects for the venture j.

Model 4 in Table 2 shows a negative and significant coefficient on the extent of dissimilarity, suggesting that the more dissimilar the VC and the venture are, the lower the assessment. This means that as similarity increases, assessment also increases. This lends strong support for Hypothesis 3.

5.5. Robustness Checks

5.5.1. Robustness Checks for Endogeneity. In our main analyses, we used VC and venture RE models to control for potential unobserved endogeneity. Next, two additional model specifications—the *simultaneous equation model and fixed effects* (*FE*) *model*—are reported to control for potential endogeneity and further check the robustness of our results. It is possible that the VC assessments could be endogenously determined since they are measured after the investment decision, and it is also possible that unobserved effects are correlated with the independent variables, making the random effects model inappropriate. We present a simultaneous equations model to address the first concern and a set of fixed effects models to address the second.

Simultaneous Equation Model. Earlier we argued that higher assessments lead to a higher probability of venture investment. Given the way our data were collected, however, it is possible that VCs were evaluating venture technical competence after making investment decisions. If so, then a standard confirmation bias effect would lead VCs to give more positive assessments to the ventures in which they chose to invest. In other words, the investment decision may drive the assessment rather than the other way around, as we have argued. To account for this potential reverse causality, we model this problem as a system of equations with instruments to assist in identifying the joint model. The general specification of the model with instruments is as follows:

$$Assess_{ij} = \alpha_0^1 + \beta^1 X_{ij} + \delta Invest_{ij}^* + \varepsilon_1, \qquad (1)$$

$$Invest_{ij}^* = \alpha_0^2 + \beta^2 Y_{ij} + \eta Assess_{ij} + \varepsilon_2, \qquad (2)$$

where $Assess_{ij}$ is VC i's assessment of the technical competence of venture j, X_{ij} and Y_{ij} are vectors of exogenous variables, and $Invest_{ij}^*$ is a latent variable that is not observable. We can observe the VC's decision to invest ($Invest_{ij}$), which can be viewed as indicator variable for which the latent variable is positive, i.e., $Invest_{ij} = 1$ if $Invest_{ij}^* > 0$, and $Invest_{ij} = 0$ otherwise. Since one dependent variable is continuous and the other is discrete in the above system of equations, we use two-stage probit least squares estimation (Alvarez and Glasgow 1999, Maddala 1983).

To identify the assessment equation, we needed an instrument that is correlated with $Invest^*_{ij}$ but not with ε_1. Two such instruments are the stock market index for technology companies (*tech index*) and the distance between the VC and venture (*distance*). We used the Morgan Stanley high technology ticker (MSH) listed on the New York Stock Exchange and used the index value at market close on the day[5] before the funding sheet was issued as the tech index. The tech index is a proxy for how positive investors feel about investing in the tech sector at that point in time. Higher index values indicate a high level of confidence in the future of the technology sector. All else being equal, as the tech index increases, VCs should be more likely to invest in technology startups. At the same time, however, we should not expect a higher tech index to correlate with VCs' assessments of any specific ventures. To calculate the distance between the VC and venture, the Haversine formula was used. This formula calculates the distance between two geographical coordinates accounting for the curvature of the Earth. The greater the distance between VCs and ventures, the less likely VCs should be to invest in ventures (Sorenson and Stuart 2001). However, there does not seem to be much reason to believe that the tech index and distance affect assessments of venture technical competence. Thus, the distance between the VC and the venture provides a second strong instrument for the assessment equation.

Similarly, to identify the investment equation, we needed an instrument that is correlated with $Assess_{ij}$ but is not correlated with ε_2. One such instrument is the number of IT certificates (such as Oracle or Microsoft certifications) completed by technical leads of ventures (*nitcert*). IT certificates may be a clearly visible and easy-to-evaluate signal of venture technical competence. Accordingly, VCs may use certifications as part of their assessment—i.e., more certifications likely indicates higher competence. At the same time, however, VCs are not likely to view the certifications on their own as reason to invest in a venture. The VC will want to carefully evaluate the extent to which the venture has the unique and focused competence required to bring its specific product or service to market. A generic certification may not be sufficient to signal that type of competence. Thus, certifications likely correlate with the VC's assessment of the venture's technical competence, but probably not with a VC's decision to invest.

Furthermore, we statistically confirm the relevance and validity of instruments by using F-statistic values and the Sargan test. To ensure that instruments are not weakly identified, we checked the F-statistic value for the first stage regression. F-statistic values were much larger than the suggested value of 10 (Staiger and Stock 1997), which suggests that instruments were not weakly identified. The Sargan test for overidentification is used to examine the orthogonality of instruments in the simultaneous model (Baum et al. 2003). The null hypothesis is that instruments are uncorrelated to errors in the model. Sargan tests failed to reject the null hypothesis ($p = 0.17$), suggesting that instruments are not highly correlated with the error term and hence satisfy the required orthogonality condition.

The results of the simultaneous equation model are shown in Model 5 of Table 3. As expected, distance negatively predicts funding, and the tech index positively predicts funding. The VC's assessment of the venture is still positive and significant. Also as expected, the number of IT certificates positively and significantly predicts the VC's assessment of the venture. The funding decision, however, does not significantly predict assessment. Thus, the simultaneous equation model lends additional support to the prior result that assessments seem to have an independent effect on the funding decision.

Fixed Effects Model. In our main analysis, we used VC and venture RE models to control for potential unobserved endogeneity. Random effects models assume that the unobserved effects are not correlated with the independent variables. To do away with this assumption, we report the results using VC and venture and FE models also. The results of the FE models are reported in Table 4 and are qualitatively similar to results of the RE models. We used both VC and venture fixed effects for Models 6 and 9 in Table 4. Model 7 provides the results of influence of venture technical competence on probability of venture failing. Since the value of the dependent variable (a dummy variable that takes the value of 1 if the venture has failed and 0 otherwise) does not change for a given venture, we cannot estimate venture fixed effects for this model. Hence, we estimate Model 7 using VC fixed effects only. Model 8 provides the results of the influence of VCs' technical competence on absolute error in assessing ventures' technical competence. If we use VC fixed effects for this model, we cannot estimate the influence of VCs' technical competence (as it does not vary for a given VC). Hence, we estimate Model 8 using venture fixed effects only.

5.5.2. Overfitting. Given the substantial controls used in the present study, we may be concerned that the statistical relationships demonstrated previously are artifacts of the highly constrained context studied here. To allay concerns with overfitting, we repeated the analyses described above using stripped-down models containing only the key explanatory variables

[5] For robustness, we also tried the average of the previous week's close as *tech index*, and the results were qualitatively similar.

Table 3 Simultaneous Equation Model

	Model 5	
	Dependent variables	
	Funding received	*Assessment*
Number of IT certificates		1.2262*** (0.4095)
Distance	−0.0014*** (0.0003)	
Tech index	0.0034*** (0.0007)	
Funding received		0.2205 (0.183)
Assessment	0.1237*** (0.023)	
Ventures' technical competence		0.3791*** (0.0317)
VCs' technical competence	−0.018 (0.0144)	−0.3138*** (0.0584)
Dissimilarity		−0.5447*** (0.0444)
Dummy reference	0.6285*** (0.0992)	0.0987 (0.4132)
Number of patents	0.0517** (0.0213)	0.181** (0.0881)
Venture team size	0.1042** (0.0418)	0.3582** (0.1444)
Market size	0.045*** (0.0153)	0.0283 (0.0506)
Competition	0.0514* (0.0279)	0.0393 (0.0953)
Founder reputation	−0.0891 (0.0663)	−0.043 (0.2077)
Founder experience	−0.0228 (0.0196)	0.0007 (0.069)
Age of a venture	0.0131 (0.0318)	−0.1439 (0.1075)
Revenue	−0.0611 (0.0451)	0.0312 (0.169)
Dummy software	−0.2729** (0.1188)	−0.0522 (0.3726)
Amount raised	0.0006* (0.0003)	0.0005 (0.001)
Amount requested	0.1084** (0.0521)	0.0504 (0.1753)
Project management experience	−0.0379 (0.0695)	1.8605*** (0.1554)
Communication	0.0039 (0.0194)	0.1687*** (0.0646)
Management capability	0.1292*** (0.0439)	0.3275** (0.1403)
VCs' failures	−0.0669*** (0.0223)	−0.0672 (0.0695)
VCs' successes	0.2605*** (0.0536)	−0.0565 (0.182)
Fund size	−0.0007 (0.0009)	−0.003 (0.0029)
VCs' experience	0.0092 (0.0168)	0.1232* (0.0732)
Total investments	0.0042 (0.018)	0.0364 (0.058)
VCs' IT experience	−0.0149 (0.0142)	−0.0695 (0.0508)
Dummy Asian VC	0.0078 (0.1136)	0.1284 (0.3878)
Dummy Hispanic VC	0.1336 (0.4031)	−1.7374 (1.1509)
VC age	−0.0094 (0.0139)	−0.0347 (0.0437)
Constant	−5.2873*** (1.0063)	16.0672*** (3.1869)
Log likelihood/R^2	−146.54368	0.6704
N	396	396

Notes. In the funding equation, ventures' technical competence is not included to see the independent effect of assessment. We thank an anonymous reviewer for suggesting this. It should be noted that including ventures' technical competence in the funding equation does not change coefficients substantially. Including dissimilarity in the funding equation also does not change results. Standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

and relevant interactions. These results are shown in Table 5. The predicted relationships still hold in these stripped-down models, suggesting that overfitting should not be a concern for our findings.

5.5.3. Connecting Dissimilarity to Investment Decisions. The logic presented in the arguments of this paper suggests that similarity may lead to higher assessment, which may subsequently lead to a higher likelihood of VC investment. Although not explicitly hypothesized in this way, we also tested the mediation hypothesis that the extent of assessment mediates the relationship between VC–venture dissimilarity and the probability of VC investment. Table 6 shows the results of this analysis. To analyze the possible complete mediation effect, four conditions need to be met (Baron and Kenny 1986). The first condition pertains to checking the association between the independent variable (*VC–venture dissimilarity*) and the dependent variable (*probability of VC investment*) without controlling for the mediator variable (*assessment*). We found that the VC–venture dissimilarity had a significant influence on the probability of VC investment without controlling for the assessment (see Model 14 in Table 6). The second condition refers to checking the association between the independent variable and the mediator variable. We found that VC–venture dissimilarity had significant influence on assessment (see Model 4 in Table 2). The third condition pertains to checking the association between the mediator variable and the dependent variable

Table 4 Fixed Effects Models

	Model 6 (for H1A)	Model 7 (for H1B)	Model 8 (for H2)	Model 9 (for H3)
	Dependent variables			
	Funding received	*Venture failure*	*Absolute error in assessing ventures' technical competence*	*Assessment*
	All observations	Only those ventures that were funded	All observations	All observations
Assessment	0.3546*** (0.0798)			
Ventures' technical competence		−0.2921*** (0.0937)		
VCs' technical competence			−0.6361*** (0.0904)	
Dissimilarity				−1.3155*** (0.1196)
Dummy reference	2.8926* (1.7570)	−0.5996 (0.5704)	−0.1281 (0.7606)	1.9279 (1.5060)
Number of patents		0.0618 (0.1616)		
Venture team size		0.074 (0.3526)		
Market size		−0.1599 (0.1145)		
Competition		0.3123 (0.2487)		
Founder reputation		0.8888 (0.8262)		
Founder experience		−0.1003 (0.1750)		
Age of a venture		−0.1365 (0.2712)		
Revenue		1.1103* (0.6233)		
Dummy software		0.3115 (0.9927)		
Amount raised		−0.001 (0.0026)		
Amount requested		0.2927 (0.4421)		
Project management experience		0.738 (0.2707)		
Communication	−0.6781* (0.3600)	−0.2829* (0.1608)	0.2823* (0.1578)	0.1908 (0.2099)
Management capability	0.5 (0.4429)	−0.1437 (0.3101)	−0.4666* (0.2524)	0.3628 (0.4879)
VCs' failures			0.1001 (0.1513)	
VCs' successes			−0.386 (0.4735)	
Fund size			−0.0041 (0.0065)	
VCs' experience			−0.043 (0.1142)	
Total investments			0.1543 (0.1385)	
VCs' IT experience			−0.0193 (0.1218)	

Table 4 (Continued)

	Model 6 (for H1A)	Model 7 (for H1B)	Model 8 (for H2)	Model 9 (for H3)
	Dependent variables			
	Funding received	*Venture failure*	*Absolute error in assessing ventures' technical competence*	*Assessment*
	All observations	Only those ventures that were funded	All observations	All observations
Dummy Asian VC			−0.1785 (0.7689)	
Dummy Hispanic VC			−0.1964 (2.4343)	
VC age			0.0875 (0.1289)	
Constant			13.9928** (6.1317)	
Log likelihood/R^2	−6.8811	−17.302	0.6428	0.8424

Notes. Including dissimilarity in Models 6, 7, and 8 also does not change results. Robust standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

after controlling for the independent variable. We found that the assessment had significant influence on the probability of VC investment (see Model 15 in Table 6). The fourth condition refers to checking the association between the independent variable and the dependent variable after controlling for the mediator variable. We found that the VC–venture dissimilarity does not influence the probability of VC investment after controlling for assessment (see Model 15 in Table 6). These results from these four conditions lend strong support to the logic that the extent of similarity between the VC and the venture affects the likelihood of investment through the mediating process of assessment. In addition, we did a statistical test suggested by Preacher and Hayes (2004) to check the significance of the indirect effect of dissimilarity. We found that the indirect effect is statistically significant ($p = \text{value} < 0.05$), indicating that assessment mediates the effect of dissimilarity.

5.5.4. Lo-VCs Driving Results. A logical conclusion from Hypothesis 2 is that lo-VCs are simply worse

Table 5 Stripped Down Models to Test Overfitting

	Model 10 (for H1A)	Model 11 (for H1B)	Model 12 (for H2)	Model 13 (for H3)
	Dependent variables			
	Funding received	Venture failure	Absolute error in assessing ventures' technical competence	Assessment
	All observations	Only those ventures that were funded	All observations	All observations
Assessment	0.1996*** (0.0328)			
Ventures' technical competence		−0.2283*** (0.0574)	−0.0202 (0.0328)	0.5351*** (0.0643)
VCs' technical competence	0.0416 (0.0335)	−0.0396 (0.0397)	−0.608*** (0.0368)	−0.395*** (0.0740)
Dissimilarity				−0.7862*** (0.0806)
Constant	−6.6514*** (1.1352)	6.0023*** (1.5505)	18.6862*** (1.2300)	24.8493*** (2.7832)
Log likelihood	−200.2723	−55.3685	−1,124.2671	−1,219.7093
N	396	120	396	396

Notes. VC and venture random effects are used in all of the models. In Model 10, ventures' technical competence is not included to see the independent effect of assessment on funding received. We thank an anonymous reviewer for suggesting this. It should be noted that including ventures' technical competence in Model 10 does not change coefficients substantially. Including dissimilarity in Models 10, 11, and 12 also does not change results. Robust standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6 Overassessment Mediating the Relationship Between Dissimilarity and Funding Probabilities

	Model 14: dissimilarity only	Model 15: both overassessment and dissimilarity
	Dependent variable: *Funding received*	
Assessment		0.1756***
		(0.0448)
Dissimilarity	−0.0732*	−0.025
	(0.0402)	(0.0417)
VCs' technical competence	−0.0639*	−0.0239
	(0.0369)	(0.0419)
Dummy reference	1.2024***	1.1642***
	(0.3382)	(0.3372)
Number of patents	0.1715**	0.1789**
	(0.0679)	(0.0702)
Venture team size	0.3882***	0.3127**
	(0.1269)	(0.1404)
Market size	0.1467***	0.1327***
	(0.0476)	(0.0491)
Competition	0.1078	0.1124
	(0.0886)	(0.0908)
Founder reputation	−0.0782	−0.0619
	(0.1726)	(0.1839)
Founder experience	−0.0353	−0.0354
	(0.0770)	(0.0721)
Age of a venture	0.0274	0.0117
	(0.1007)	(0.1047)
Revenue	−0.0206	−0.0299
	(0.1899)	(0.1791)
Dummy software	−0.4381	−0.4015
	(0.3392)	(0.3122)
Amount raised	0.0022**	0.002*
	(0.0011)	(0.0011)
Amount requested	0.1757	0.1643
	(0.1566)	(0.1772)
Project management experience	0.4537***	0.0419
	(0.0852)	(0.1402)
Communication	0.003	−0.0359
	(0.0529)	(0.0561)
Management capability	0.2851**	0.2575*
	(0.1387)	(0.1426)
VCs' failures	−0.0984**	−0.0916**
	(0.0387)	(0.0413)
VCs' successes	0.4417***	0.4704***
	(0.1061)	(0.1125)
Fund size	−0.0021	−0.0022
	(0.0018)	(0.0019)
VCs' experience	0.0694**	0.0599*
	(0.0315)	(0.0339)
Total investments	−0.0414	−0.0408
	(0.0390)	(0.0416)
VCs' IT experience	−0.036	−0.0143
	(0.0263)	(0.0296)
Dummy Asian VC	0.2325	0.0864
	(0.2044)	(0.2590)
Dummy Hispanic VC	−0.0273	0.2386
	(0.3277)	(0.4080)
VC age	−0.0263	−0.0243
	(0.0279)	(0.0288)
Constant	−4.6524**	−8.1715***
	(2.2985)	(2.3066)
Log likelihood	−170.5422	−158.1698
N	396	396

Notes. VC and venture random effects are used in all the models. In Models 14 and 15, ventures' technical competence is not included to see the independent effect of assessment on funding received. We thank an anonymous reviewer for suggesting this. It should be noted that including ventures' technical competence in Models 14 and 15 does not change coefficients substantially. Robust standard errors are in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

at evaluating technical competence than hi-VCs. If lo-VCs are purely random in their errors, then this should not threaten the results presented previously. However, it is possible that lo-VCs have a cognitive anchor around medium levels of technical competency that serves as their default assessment of venture technical competence. Thus, rather than assessing ventures randomly throughout the competency spectrum, they may cluster their assessments around some medium competence level. If so, then lo-VCs will systematically overassess lo-ventures, because their true technical competence falls below the medium competency anchor, and they will systematically underassess hi-ventures, because their true technical competence is above the medium competency anchor. Thus, if lo-VCs anchor their bad assessments around a medium level of technical competency, we can logically deduce the results of H3. In other words, the apparent dissimilarity between lo-VCs and hi-ventures correlates with underassessment, and apparent similarity between lo-VCs and lo-ventures correlates with overassessment. Thus, the results observed in H3 could be artifacts of the data driven by variance in lo-VC assessments rather than a true similarity effect.

To refute this possibility, we recreated our analysis by using only the top third of VCs in technical competence. If we include only hi-VCs, then the logic described above no longer holds. As shown in Table 7, the results are qualitatively similar, suggesting that the variance in lo-VC ratings are not driving the supportive results for H3.

5.5.5. Similarity Between the VC and Venture in Other Dimensions. It is also plausible that similarity between the VC and technology head in aspects other than technical competence can also have significant influence on the VC's assessment. Following this literature, we added age similarity and education background similarity as controls and redid our analysis

Table 7 Analysis with High-Technical-Competence VCs

	Model 16 (for H1A)	Model 17 (for H2)	Model 18 (for H3)
	Funding received	*Absolute error in assessing ventures' technical competence*	*Assessment*
Assessment	0.2266*** (0.0593)		
Ventures' technical competence		0.0109 (0.0308)	0.7630*** (0.0470)
VCs' technical competence	0.7155*** (0.2103)	−0.2514*** (0.0912)	−0.2041 (0.3385)
Dissimilarity			−0.2062*** (0.0679)
Dummy reference	0.9558 (0.7473)	0.2003 (0.3883)	−0.9697 (0.6281)
Number of patents	0.2699** (0.1329)	0.1031* (0.0551)	0.3366*** (0.1299)
Venture team size	0.3613 (0.3223)	−0.0179 (0.1196)	0.2126 (0.2162)
Market size	0.2420* (0.1354)	0.0319 (0.0445)	−0.0648 (0.0848)
Competition	0.3895 (0.2412)	0.0936 (0.0911)	0.0182 (0.1650)
Founder reputation	0.1852 (0.5421)	−0.223 (0.2499)	−0.0542 (0.3514)
Founder experience	−0.1468 (0.1853)	−0.0618 (0.0880)	0.1273 (0.1203)
Age of a venture	−0.1125 (0.1624)	−0.1185 (0.1072)	0.0397 (0.1956)
Revenue	−0.7319* (0.4219)	−0.156 (0.2554)	−0.4517 (0.3118)
Dummy software	0.2965 (0.6283)	0.0363 (0.2291)	0.6562 (0.5837)
Amount raised	0.0017 (0.0020)	−0.001 (0.0009)	0.0028* (0.0017)
Amount requested	1.0610*** (0.3671)	0.4355*** (0.1195)	−0.2347 (0.2752)
Project management experience	0.1432 (0.2664)	0.1433 (0.1134)	1.4372*** (0.2034)
Communication	−0.2592** (0.1242)	−0.0382 (0.0554)	0.2046* (0.1072)
Management capability	0.2787 (0.2988)	−0.0147 (0.1250)	0.2879 (0.1960)
VCs' failures	−0.1785 (0.3848)	0.2916** (0.1155)	0.0088 (0.4656)
VCs' successes	−0.8418*** (0.2995)	0.2537*** (0.0903)	−0.1277 (0.4805)
Fund size	−0.0192** (0.0086)	0.0051*** (0.0020)	−0.0009 (0.0099)
VCs' experience	−0.6298* (0.3362)	0.1225 (0.0825)	0.0465 (0.4366)
Total investments	0.2472** (0.0999)	−0.0929*** (0.0270)	−0.002 (0.1579)
VCs' IT experience	0.2936** (0.1278)	0.0087 (0.0259)	−0.1669 (0.1509)
Dummy Asian VC	0.2669 (0.9091)	−0.4529* (0.2612)	0.2139 (0.9717)
Dummy Hispanic VC	4.3965* (2.4121)	−0.6055 (0.3741)	−1.3581 (2.6917)

Table 7 (Continued)

	Model 16 (for H1A)	Model 17 (for H2)	Model 18 (for H3)
	Funding received	*Absolute error in assessing ventures' technical competence*	*Assessment*
VC age	0.0966	0.0147	−0.077
	(0.0845)	(0.0270)	(0.1295)
Constant	−27.9632**	6.5447	10.5799
	(12.4178)	(4.1542)	(15.0880)
Log likelihood	−52.8405	−266.6231	−344.3975
N	137	137	137

Notes. VC and venture random effects are used in all of the models. In Model 16, ventures' technical competence is not included to see the independent effect of assessment on funding received. We thank an anonymous reviewer for suggesting this. It should be noted that including ventures' technical competence in Model 16 does not change coefficients substantially. Including dissimilarity in Models 16 and 17 also does not change results. Robust standard errors are in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

(Franke et al. 2006). These data were available for only 74% of VC–venture pairs. Age similarity is defined as the absolute difference in ages of the VC and the technical lead. Educational background (management or technology) similarity is operationalized as a dummy variable, which is coded as 1 if the technical lead and VC have similar educational training and 0 otherwise. The results of this analysis are reported in Table 8 and are qualitatively similar to results reported earlier. It is also important to note that these other similarity measures do not significantly predict a VC's funding decision. They may have predicted the decision to invite ventures for presentations, but our data do not allow that analysis.

5.6. Results Summary

As expected, we find that VC assessments of venture competence strongly correlate with VC investment decisions, that venture technical competence strongly correlates with venture failure, that VC technical competence strongly correlates with assessment accuracy, and that similarity in technical competence strongly predicts positive assessment bias. These findings are robust to multiple specifications and numerous robustness checks.

6. Discussion and Conclusion

6.1. Implications for Theory and Future Research

Using a unique and proprietary data set, we have shown that higher VC technical competence predicts higher accuracy in evaluating the technical competence of ventures, and that higher similarity between the VC and venture in technical competence leads to higher assessments by the VC. We also show that this higher assessment leads to a greater likelihood of VC investment. Accordingly, greater similarity between the VC and the venture in technical competence may lead to the VC being more likely to invest in ventures that are more likely to fail. Our work, therefore, joins the growing conversation exploring potential shortcomings in VC investment decisions (e.g., Franke et al. 2006, 2008; Guler 2007).

One important way our work differs, however, is by exploring a deeper form of similarity than has been explored previously. Rather than testing whether similarity in high-level demographic factors leads to ex ante bias, we explore the extent to which actual similarity in technical competence leads to positive bias through real social interactions. We have argued that decision makers may update their initial assessments through actual social interactions and that those decision makers may be more attuned to deeper similarities in social interactions than simple demographics. We have shown that similarity in technical competence does lead to positive assessment bias, and our results lend support to our proposed mechanisms. Specifically, our results support the notion that similarity in technical competence creates a shared language between the VC and the venture that helps to smooth interpersonal interactions and create more positive relationships. This positivity likely drives the positive assessment bias. Thus, whereas prior work explores the effects of apparent similarity on ex ante decisions (Franke et al. 2006), our research focuses on the effects of actual similarity on social interactions and subsequent decision outcomes.

We have examined similarity in technical competence because it is a centrally important factor in VC investment decisions for technology ventures, but it is possible that other kinds of similarity may have similar or related effects. We have controlled, for example, for managerial capability in our empirical models. Given the importance of business acumen for actually brining technical innovation to market, it is possible that similar managerial capabilities may also lead to positive bias. Future research may more carefully explore the extent to which similarities in other kinds of competence may lead to biased judgments.

Table 8 Robustness Check Controlling for VC and Venture Similarity

	Model 19 (for H1A)	Model 20 (for H1B)	Model 21 (for H2)	Model 22 (for H3)
	Dependent variables			
	Funding received	*Venture failure*	*Absolute error in assessing ventures' technical competence*	*Assessment*
	All observations	Only those ventures that were funded	All observations	All observations
Assessment	0.1919*** (0.0433)			
Ventures' technical competence		−0.4685*** (0.0890)	−0.0332 (0.0381)	0.3759*** (0.0642)
VCs' technical competence	−0.0376 (0.0532)	0.065 (0.0987)	−0.6769*** (0.0571)	−0.3336*** (0.0558)
Dissimilarity				−0.5239*** (0.0822)
Age similarity	−0.0046 (0.0332)	−0.0263 (0.0638)	−0.0377 (0.0476)	0.0228 (0.0383)
Education similarity	0.0366 (0.3396)	−1.9495*** (0.7223)	−0.4461 (0.5124)	−0.3949 (0.5134)
Dummy reference	0.8621** (0.3784)	−0.7279 (0.6866)	0.9765*** (0.3489)	0.4374 (0.4289)
Number of patents	0.177* (0.0952)	0.0691 (0.1523)	0.0233 (0.0974)	0.1441 (0.0940)
Venture team size	0.4525*** (0.1450)	0.4826 (0.3668)	−0.0718 (0.1887)	0.1423 (0.1899)
Market size	0.1388*** (0.0507)	−0.2214* (0.1221)	0.0152 (0.0762)	0.1** (0.0445)
Competition	0.1076 (0.0953)	0.2185 (0.2017)	−0.054 (0.1162)	0.1153 (0.1154)
Founder reputation	−0.0819 (0.2043)	−0.1735 (0.6058)	−0.1036 (0.2329)	−0.2071 (0.2864)
Founder experience	−0.0358 (0.0629)	−0.3366** (0.1378)	−0.0383 (0.0908)	−0.0589 (0.1200)
Age of a venture	0.0331 (0.1054)	0.3214 (0.3523)	−0.1085 (0.1280)	−0.1041 (0.1232)
Revenue	−0.1337 (0.2004)	0.4595 (0.4215)	0.0011 (0.2128)	−0.0224 (0.2639)
Dummy software	−0.3935 (0.4064)	0.8308 (0.9861)	−0.8478* (0.4895)	−0.0283 (0.5814)
Amount raised	0.0023* (0.0013)	0.0004 (0.0022)	−0.0013 (0.0012)	0.0016 (0.0015)
Amount requested	0.0732 (0.1873)	0.1317 (0.3789)	0.7543*** (0.2325)	0.0955 (0.1766)
Project management experience	−0.042 (0.1406)	0.6576 (0.2684)	−0.1298 (0.1973)	2.4079*** (0.2171)
Communication	−0.0579 (0.0443)	−0.0336 (0.1221)	0.2409** (0.1130)	0.1317 (0.1177)
Management capability	0.18 (0.1572)	0.0755 (0.2031)	0.3766** (0.1817)	0.4433** (0.1911)
VCs' failures	−0.0879 (0.0613)	0.437** (0.1836)	−0.1651** (0.0823)	−0.0868 (0.0782)
VCs' successes	0.5664*** (0.1432)	−0.3571 (0.4051)	0.2296 (0.1433)	−0.0265 (0.1416)
Fund size	−0.001 (0.0031)	−0.0039 (0.0045)	0.0017 (0.0033)	−0.0024 (0.0024)
VCs' experience	0.0686 (0.0513)	0.2341 (0.1944)	0.039 (0.0805)	0.1012 (0.0689)
Total investments	−0.0401 (0.0552)	−0.1168* (0.0704)	0.0919 (0.0685)	0.0214 (0.0493)

Table 8 (Continued)

	Model 19 (for H1A)	Model 20 (for H1B)	Model 21 (for H2)	Model 22 (for H3)
	Dependent variables			
	Funding received	*Venture failure*	*Absolute error in assessing ventures' technical competence*	*Assessment*
	All observations	Only those ventures that were funded	All observations	All observations
VCs' IT experience	−0.0299	−0.1694*	0.0624	−0.1202***
	(0.0406)	(0.1008)	(0.0439)	(0.0289)
Dummy Asian VC	0.2221	1.1548*	0.8563*	0.5821*
	(0.4106)	(0.6283)	(0.4788)	(0.3360)
Dummy Hispanic VC	0.5117	−2.0273	−0.8906	−2.0755**
	(0.5703)	(1.9093)	(0.8203)	(1.0082)
VC age	−0.0008	0.1362	−0.0718	−0.0511
	(0.0452)	(0.1055)	(0.0561)	(0.0533)
Constant	−8.3211**	−2.7797	18.8001***	18.4445***
	(3.3841)	(5.9553)	(3.6468)	(3.1093)
Log likelihood	−126.8814	−34.8776	−803.2231	−805.7582
N	293	119	293	293

Notes. VC and venture random effects are used in all of the models. In Model 19, ventures' technical competence is not included to see the independent effect of assessment on funding received. We thank an anonymous reviewer for suggesting this. It should be noted that including ventures' technical competence in Model 19 does not change coefficients substantially. Including dissimilarity in Models 19, 20, and 21 also does not change the results. Robust standard errors are in parentheses.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

We also contribute theoretically to the VC investment decision literature by partially explaining why some VCs may be better able to assess the technical competence of ventures than others. By so doing we directly challenge the implicit assumption in prior work that VCs are similar in their abilities to evaluate venture technical competence. Thus, although prior research has clearly established the theoretical importance of venture technical competence for venture performance outcomes (e.g., Colombo and Grilli 2005, Kor 2003), our work suggests that measures of venture technical competence are not sufficient for explaining VC investment decisions. Instead, we must more carefully explore why some VCs are better able to evaluate and predict venture technical competence. Thus, the ability to assess accurately may be an important factor explaining why some VCs systematically outperform others in their investment decisions.

6.2. Managerial Implications

Our findings are also substantively important for practicing managers given the significance of these ventures for economic growth and development. Eleven percent of private-sector jobs come from venture-backed companies, and venture-backed revenue accounts for 21% of U.S. gross domestic product (National Venture Capital Association 2011). The VC domain has a substantial footprint (National Venture Capital Association 2011), roughly equal to the combined size of three widely researched industry domains—the online book domain (*Publishers Weekly* 2011), the box-office domain (Motion Pictures Association of America 2011), and the music domain (Friedlander 2011). One VC-industry-specific implication of this study is that there may be a need to structure the evaluation of ventures' technical competence so that VCs can rely on actual assessments, rather than their own imperfect approximations. The VC industry traditionally relies on VCs to evaluate ventures' technical competence using their own idiosyncratic methods, but this may not be the best solution. Introducing somewhat standard and objective assessments of technical competence within certain domains may help VCs reduce their reliance on potential decision biases when determining the ventures in which to invest.

Our work also implies that founders of technology ventures would benefit from ensuring a high level of technical competence on the venture team. Our findings are consistent with prior research suggesting that technical competence enhances venture survival. Where our work adds to prior implications, however, is by showing that a highly competent technology head can facilitate more positive social interactions with competent VCs. In addition to having a positive effect on VC funding decisions, these positive relationships may also affect the VC's propensity to invest time and other resources into the venture's survival. Future research may also explore the extent to which similarity in technical competence affects the VCs level of nonmonetary investment in the venture.

6.3. Limitations

Although we have included many controls and tested multiple specifications, our empirical design nevertheless suffers from several important limitations. First, there are several omitted controls, due to data availability, that may have improved the robustness of our work. Specifically, we may have benefited from a measure of the number of ventures started by founders before the current ventures. This control would have helped to alleviate the potential concern that serial entrepreneurs may be more likely to receive funding, ceteris paribus.

Second, despite our efforts to deal with endogeneity through a simultaneous equation model, there is still a flaw in the timing of our data collection that empirical tests cannot fully rectify. Specifically, we gathered VC assessments after VCs made investment decisions. A superior design would have measured assessments of technical competence at the time of the venture presentation so that the temporal ordering of data collection would have made clear the independent effect of the assessment on subsequent decision outcomes. Although this may have been a superior approach, it was not possible in this case. Despite this shortcoming, however, we note that the strong independent effect of assessment on subsequent investment decisions persisted even in the simultaneous equation model. Accordingly, we believe our data and results lend positive support to our core hypotheses.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2117.

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