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Strike a Happy Medium: The Effect of IT Knowledge on Venture Capitalists' Overconfidence in IT Investments[1]

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In this article, the effect of IT knowledge on the overconfidence of venture capitalists (VCs) in their IT investments is examined. Our findings show that the effect of IT knowledge on overconfidence is nonlinear. VCs with moderate levels of IT knowledge are least overconfident. At the same time, VCs with moderate levels of IT knowledge are most resistant to the biasing effects of past successes. Past failures show a negative association with overconfidence independent of the level of the VC's IT knowledge. Finally, the negative association between stakes and VC overconfidence is stronger with greater levels of IT knowledge. These results shed light on the highly disputed role of IT knowledge in the domain of IT investments.

Keywords: IT knowledge, overconfidence, IT startups, IT investments, venture capital

"The more tech knowledge we have, the better we can predict ventures' outcomes."
A reputed venture capitalist in the IT domain

Introduction

The venture capital industry has been raising $20–30 billion dollars yearly for the past decade. IT-based startups form the largest portion of investments backed by venture capitalists (VCs), accounting for more than one-third of the investments of the total venture capital industry. Many successful information technology (IT) companies such as Microsoft, Apple, Google, Facebook, Twitter, and Uber started as VC-funded startups. Accolades are often heaped onto the venture capital industry for creating great IT ventures. However, the trade press routinely debates whether VCs are justified to be as optimistic as they are in evaluating IT startups (Austin 2010;

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Economist 2011). The academic literature further brings empirical evidence of VCs' significant overconfidence. For instance, Zacharakis and Shepherd (2001) found that the vast majority of VCs in their study exhibited overconfidence in judging venture success.

Overconfidence, one of the biggest villains of decision making (Heath and Heath, 2014), has long been shown to lead to poor financial decisions by investors and managers alike (Barber and Odean 2000; Benos 1998; Cheng 2007; Daniel et al. 1998; Odean 1998). Overconfidence in investors leads them to trade more frequently (Barber and Odean 2000; Cheng 2007; Glaser and Weber 2007; Graham et al. 2009; Odean 1998, 1999), bear greater levels of risk (Odean 1998), disregard information more (Cooper et al. 1995; Harvey 1994; Mahajan 1992), fail to prepare for possible adversity, and consequently loose more money than their peers (Cheng 2007; Odean 1998, 1999). When managers are overconfident they use less external finance (Malmendier et al. 2011), overspend in corporate investments (Malmendier and Tate 2005), initiate value destroying acquisitions (Billett and Qian 2008), and delay needed strategic change in response to poor firm performance (Park et al. 2011). The worst part of overconfidence is that it robs investors of the realization that they may be mistaken and tricks them into making more of such financial mistakes (Belsky and Gilovich 2010). Further, overconfidence is more likely in environments that are highly uncertain, stressful, and characterized by time pressure and information overload, which is exactly the type of environment faced by VCs (Bygrave 1988; Kunze 1990). Extant studies suggest that this type of environment fosters decision errors, including the overconfidence bias (Baron 1998; Busenitz and Barney 1997).

There has been significant scholarly interest in understanding the investment decisions of venture capitalists with an increased scrutiny of possible decision biases (Dimov 2007; Franke et al. 2006; Petty and Gruber 2011; Rosenbusch et al. 2013). Specifically, overconfidence has been shown to negatively affect VCs' decision accuracy (Ács and Audretsch 2006; Zacharakis and Shepherd 2001). VCs typically reject a large number of funding proposals, many times after a brief consideration of only a few minutes (Cumming 2012). Therefore, overconfidence in decisions keeps VCs from realizing that they can benefit from more due diligence before refusing a venture. On the contrary, if a venture passes an initial screening, it has a good chance of getting funded as VCs' overconfidence in their decisions may lead them to not thoroughly question ventures (Yazdipour 2010). Overconfidence tricks VCs to limit their information search and keeps them from identifying concerns that portray a less-enthusiastic outlook of their investment decisions (Zacharakis 1997). In addition, just as in other domains, research suggests that VCs' overconfidence inhibits their learning and prevents them from improving their decision processes (Ács and Audretsch 2006; Cumming 2012). VCs' misplaced confidence ultimately hurts everyone in the system—VCs lose reputation, limited partners lose money, and the society fails to grow jobs. Hence, reasons that lead to VC overconfidence in investment decisions merit further research attention.

Many studies suggest that an increase in knowledge decreases overconfidence and makes individuals better at recognizing the limits of their knowledge (Dunning 2011; Ehrlinger et al. 2008). Experts are better able to foresee uncertainties around their decisions because of their fine-grained domain knowledge (Gladwell 2007; Sternberg and Grigorenko 2003). Theories of expert knowledge suggest that VCs with greater technical knowledge should better assess their technology investment decisions (Castanias and Helfat 2001; Eisenhardt and Schoonhoven 1990; Kor 2003; Shepherd et al. 2003). Past research seems to have taken VCs' technical expertise for granted and has assumed that VCs are fully capable of understanding technical aspects of ventures when making investment decisions in IT startups. If all VCs are equally able to comprehend the technical aspects of technology ventures, then the lack of research should not be concerning. However, anecdotal evidence suggests otherwise. For example, two noteworthy VCs, Bart Stuck and Michael Weingarten (2004), have expressed their concern about the lack of IT knowledge among VCs: "Many [VC funds] are populated with MBA types who understand business but don't really understand technology at an in-depth level." Apparently, VCs vary in their technical expertise and their ability to see technical uncertainties associated with their technology investment decisions.

Past work has assumed the relationship between knowledge and overconfidence to be linear and has reported conflicting results (Koehler et al. 2002; Skala 2008). Many studies compare expert stock market investors with nonexperts, and suggest that overconfidence increases with knowledge (Bradley 1981; Olsen 1997). Highly knowledgeable investors in stock markets are known to overestimate their abilities, leading to overconfidence in their investment decisions (Glaser and Weber 2010; Montier 2010). Perhaps these studies have compared moderately knowledgeable with highly knowledgeable on a knowledge continuum, while studies that have predicted overconfidence to decrease with knowledge (Dunning 2011; Ehrlinger et al. 2008) have compared less knowledgeable with moderately knowledgeable on a knowledge continuum.

In this research, we explain these contradictory results reported in the literature and suggest that VCs' technical knowledge has a U-shaped relationship with overconfidence in their technology investments. A few extant consumer behavior studies corroborate this "happy medium" view. As Bettman and Park (1980) and Crotts (1999) find, the moderately knowledgeable do more processing of the currently available information for making a product choice than do those with a low or a high knowledge base. Whereas those with low knowledge may not have the ability necessary to process information, the highly knowledgeable may not have the motivation to do so because they feel they have enough prior knowledge on which to rely. A similar complacency in learning new product information is found by Wood and Lynch (2002) for those with high prior knowledge. To the best of our knowledge, there is scarcity of work that examines possible nonlinear effects of knowledge on overconfidence in decision making broadly speaking, and within the field of IT investments specifically.

Further, VCs' IT knowledge may moderate the effects of other aspects of the decision making environment, such as past successes, failures, and stakes. We use the framework of the illusion of knowledge (Dunning 2011; Kruger and Dunning 1999; Miller and Ross 1975) to provide theoretical arguments for nonlinear and interaction effects of IT knowledge on VC overconfidence. Our findings provide a more nuanced picture of the role of IT knowledge and shed light on the disputed role of IT knowledge for VCs in the IT domain (Smaltz et al. 2006; Tucci 2007).

With millions of dollars at stake, VCs have strong incentives to avoid any systematic judgment biases. Therefore, our research hypotheses are subjected to strict falsifiability. As Massey and Thaler (2013, p. 1479) note,

> A question of increasing interest to researchers in a variety of fields is whether the biases found in judgment and decision making research remain present in contexts in which experienced participants face strong economic incentives.

One of the strengths of this study is the richness of the fine-grained data gathered from VCs. The data section describes this in more detail. The venture-funding context investigated in this work is of significant importance. Eleven percent of private sector jobs come from venture backed companies, and venture backed revenue accounts for 21 percent of U.S. GDP (NVCA 2011b). VC domain is a big industry (NVCA 2011a), and is roughly equal to the combined size of three widely researched industry domains: online books (BookStats 2011), box-office (MPAA 2011), and music (Friedlander 2011).

Theory and Hypothesis Development ■

The Role of IT Knowledge

From Confucius to Socrates to modern times, the secret of a truly wise decision maker has been understood as knowing both what one knows and what one does not know (Russo and Schoemaker 1992). Management research, however, documents a pervasive tendency of individuals to fail in understanding the limits of their knowledge in a variety of business domains (Griffin and Varey 1996). In this work, we refer to such overassessment of one's knowledge as the illusion of knowledge. For example, CEOs who show a greater tendency to overestimate their managerial ability tend to be overly confident in initiating mergers that destroy shareholder value (Malmendier and Tate 2008). The effect is particularly pronounced in firms with abundant internal resources because CEOs can act easily on their inflated perceptions of ability. In experimental markets, an overly optimistic assessment of one's skill leads to overconfidence in assessing the benefits of market entry, and more so when an individual self-selects into games in which the payoff will depend on skill level rather than chance (Camerer and Lovallo 1999). Because in masculine domains such as financial investments, men are known to show a greater illusion of knowledge than women (Lundeberg et al. 2000), this gender difference in self-assessment has been shown to produce a difference in how overconfident investors appear to be in their common stock investments (Barber and Odean 2001). To sum up, a variety of research studies show that the greater the illusion of knowledge, the more the overconfidence in one's decisions (Bjork 1999).

In the context of IT investments, VC confidence in new business ventures relates to whether they believe their IT knowledge is high, as is evidenced in the opening quote of this paper by a reputed venture capitalist: "The more tech knowledge we have, the better we can predict ventures' outcomes." Yet, as the above discussion suggests, the danger lies in a potential overestimation of one's IT knowledge as VCs who overestimate their IT knowledge to a greater extent may be unrealistically optimistic about the success of their investments (Russo and Schoemaker 1992). For example, VCs who are mistaken about their technical knowledge may overassess their ability to evaluate the founding team and to recruit strong technical talent (Gorman and Sahlman 1989). They may be less inclined to bring in technical consultants when needed and be less likely to compromise during negotiations with technical vendors because the illusion of knowledge has also been shown to affect how individuals seek information and how they conduct business negotiations (Bazerman and Neale 1982; Russo and Schoemaker 1992; Yaniv 2004). They may get carried away with technical verbiage and fail to discern the value of the underlying technology over competing technologies. They may set wrong expectations about future product releases and underestimate time to implement new features. The fairly straightforward implication with the illusion of knowledge is that the decision makers act on their rosy perceptions of reality rather than on reality itself (March 1994). As a result, VCs with high illusion of IT knowledge are likely to produce overconfident valuations of the firms they fund.

On the one hand, less knowledgeable decision makers are known to succumb more to the illusion of knowledge in comparison to those who are moderately knowledgeable (Alter et al. 2010). For example, in a study of medical doctors, poor performers were found to grossly overestimate their knowledge and problem solving ability and produce self-ratings that resembled those of good performers (Haun et al. 2000). In studies with undergraduate students, those performing in the bottom 25 percent were found to believe that they are performing above the 60^{th} percentile (Kruger and Dunning 1999). Similarly, VCs with low IT knowledge should more likely overestimate their IT knowledge compared to VCs with moderate IT knowledge. They may not know enough to recognize the limits of what they know and their view of the IT domain may be overly abstract, producing a mere illusion of understanding (Alter et al. 2010).

On the other hand, highly knowledgeable decision makers are also known to be a more likely target of positive illusions due to their use of automated intuitive reasoning processes as opposed to the more deliberative information processing characteristic of those with moderate levels of IT knowledge (Shiffrin and Schneider 1977; Slovic et al. 1985). Once thinking becomes more automated and intuitive, information processing happens quickly leaving little time for critical analysis of decisions taken. Intuitive reasoning is accompanied by a perception of little apparent effort (Hogarth 1987). The knowledge is not evaluated critically unless efforts are made for the specific purpose of questioning its limits. Familiarity of domain also incites automated reasoning processes and a higher illusion of knowledge (Koriat et al. 1980). The resulting ease with which judgments are produced in the familiar IT domain for VCs with high IT knowledge is likely to lead to the illusion of knowledge because VCs who are highly knowledgeable in technology are likely to find the technical evaluation exercise more familiar than VCs who are moderately knowledgeable in IT. They are less likely to engage in self-insight questioning and rely more on automative reasoning process. Therefore, more knowledgeable VCs should show a higher illusion of knowledge than those with moderate IT knowledge. There is some research examining the behavior of stock market investors that lends support to this conjecture. For example, highly knowledgeable investors in stock markets are known to overestimate their abilities, leading to overconfidence in their investment decisions (Glaser and Weber 2010; Montier 2010).

Thus, we argue that both VCs with low and high levels of IT knowledge will more likely succumb to the illusion of knowledge than VCs with moderate levels of IT knowledge. The relationship between IT knowledge and the illusion of IT knowledge is U-shaped. We also argued earlier that the illusion of IT knowledge should produce overconfidence. Therefore, the relationship between IT knowledge and overconfidence should be U-shaped as well. VCs with both low and high levels of IT knowledge will be more likely to overestimate their ability to overcome the adversities of the business environment of an IT start-up due to their overly positive and unrealistic view of how much they know about the IT domain. As a result, they will produce excessively optimistic assessments of the future of firms they chose to fund.

> *Hypothesis 1: IT knowledge has a U-shaped relationship with VC overconfidence in their IT investments.*

The Role of Past Successes and Failures

The old aphorism "a rising tide lifts all boats" does not seem to have wide acceptance among investors. Investors are often quick to attribute market-wide gains to their knowledge and ability, and are more likely to invest with much greater confidence after a successful spell (Gervais and Odean 2001). Indeed, Billett and Qian (2008) bring evidence of CEO overconfidence in acquisitions stemming from past successes and the operation of the self-attribution bias. Professional forecasters also seem to become more overconfident following a successful forecast. They begin to erroneously rely to a greater extent on their private knowledge rather than alternative sources of information, to the detriment of forecast quality (Deaves et al. 2010; Hilary and Hsu 2011; Hilary and Menzly 2006). In a similar vein, past successful investments are likely to induce overconfidence in VCs. Gino and Pisano (2011) suggest that past success is an important contributing factor largely due to the classical self-serving attribution bias (Miller and Ross 1975). The self-serving attribution bias refers to the tendency of decision makers to more readily take credit for past success than for past failure (Mezulis et al. 2004). The bias is also known to be particularly strong when outcomes are ego-involving or important (Miller 1976). As a result, decision makers may not feel the need to engage in careful scanning of their environments to identify alternative explanations for success.

On the contrary, past failures offer an opportunity to reckon our illusions about self. Failed funded IT startups should motivate VCs to reflect on their funding decisions, providing an opportunity for self-insight; thus, failed investments should decrease VCs' overconfidence. Gervais and Odean (2001) lend support to the idea that past failures decrease overconfidence. In particular, they theorize that, after facing a failure, investors may question their ability and trade less. To sum up, past successes should increase overconfidence in VCs while past failures should decrease it.

Heath and Tversky (1991), however, point to an important peculiarity in attributions. They suggest that attributing past successes to one's own knowledge while ascribing past failures to external factors is more likely for those who consider themselves to be highly knowledgeable. Those who question the limits of their knowledge may not as readily attribute past successes to their knowledge and failures to reasons beyond their control. Individuals in general are motivated to interpret results in a flattering way as it fosters a positive view about self and mental well-being (Taylor and Brown 1988). They may engage in self-protective attributions under conditions of past failure (Miller and Ross 1975). They may not completely shoulder the blame of failure on self. Thus, misperceptions about one's own knowledge makes it easier to attribute positive results to one's own abilities and negative outcomes to external causes. If individuals are unaware of how misplaced their self-assessments are, they may not have the motivation to diagnose the discrepancy in attributions (Duval and Silvia 2002). Individuals with a higher illusion of knowledge thus should have less of a motivation to question self-enhancing attributions under success and exhibit more self-enhancing attributions under failures. Indeed, overconfidence has been reported to be greater for investors with greater misperceptions about their knowledge (Glaser and Weber 2010; Montier 2010). The study by Knauff et al. (2010) of stock brokers also lends support to this view. They found that those who believe themselves to be highly knowledgeable showed persistence in following their knowledge beliefs even at the cost of making irrational choices. If VCs have illusions about their IT knowledge, they should be highly motivated to protect that illusion. The higher the illusion and the bigger the opportunity posed by a past success, the more the motivation to welcome this success by attributing success to one's own ability. On the other hand, the higher the illusion and the bigger the threat posed by a past failure, the more the motivation to fend off this threat by ascribing failure to reasons beyond one's control. Therefore, the greater illusion of IT knowledge should strengthen (weaken) the biasing (de-biasing) effect of past successes (failures) on VCs' overconfidence in their funded ventures.

We earlier argued that the relationship between IT knowledge and the illusion of IT knowledge is U-shaped. Thus, we predict that IT knowledge should moderate the effect of success and failure on overconfidence in the following way: Because VCs with low levels of IT knowledge and high levels of IT knowledge may both succumb to the illusion of IT knowledge to a greater extent, they are also less likely to resist the biasing effects of past successes compared to VCs with moderate levels of IT knowledge. There should be a stronger positive relationship between past successes and overconfidence for VCs with low and high levels of IT knowledge compared to VCs with moderate levels of IT knowledge. In other words, when the level of IT knowledge increases from low to moderate, we expect the biasing effect of past successes to diminish. Yet, as the level of knowledge increases from moderate to high, the biasing effect of past successes may increase. On the other hand, failures may exert a weaker de-biasing effect on VCs who have low and high IT knowledge, but a stronger effect on those who have moderate levels of IT knowledge. When the level of IT knowledge increases from low to moderate, we expect the de-biasing effect of past failures to strengthen. Yet, as the level of knowledge increases from moderate to high, the de-biasing effect of past failures may become weaker.

Hypothesis 2: The positive (negative) effect of past successes (failures) on overconfidence in IT investments first decreases (increases) and then increases (decreases) with an increase in IT knowledge.

The Role of Stakes

Another important feature of the decision-making environment has to do with the stakes associated with accurate judgment (Hogarth 2001). VCs may be motivated to a different extent to assess ventures accurately depending on the amount of funding required. Indeed, individuals should engage in greater information gathering and information processing efforts when more is at stake in a given decision (Hammond et al. 1999). Thus, greater stakes are more likely associated with more systematic and deliberative thinking targeted at producing more accurate judgments (Chaiken 1980; Chaiken and Maheswaran 1994).

At the same time, Vroom (1964) suggests that decision maker's knowledge level is an important moderator of the effects of stakes. The greater motivation by itself may not be enough to produce accurate judgments. This is particularly true in the context of IT investments. An individual has to possess the technical knowledge necessary to produce accurate judgments. Thus, we expect that it is more likely that the increased motivation due to higher stakes would enable a more accurate judgment on the part of VCs who have greater levels of IT knowledge. Note that VCs with low levels of IT knowledge, despite their high motivation, would be simply less capable of understanding technology concerns that may inhibit projected growth. Hence, they are likely to show unwarranted optimism. Because the effect of stakes is moderated by the actual availability of knowledge rather than the individual's subjective assessment of their knowledge, we do not expect any nonlinearity in the shape of the relationship between stakes and overconfidence at different levels of VCs' IT knowledge. Thus,

> *H3: The effect of stakes on overconfidence in IT investment increases with an increase in IT knowledge.*

Data

To test our hypotheses we require data on VCs' IT knowledge, successes, failures, and stakes in investment, along with over-valuation of IT investments and a host of control variables. Since such data was not publicly available, we approached VCs directly to collect the data for our study. Accordingly, our data constitutes a unique and proprietary data set allowing us to examine the influence of IT knowledge on VC overconfidence.

We sent data requests in January 2009 to a random sample of 200 VCs who invest in early-stage IT ventures from the VentureXpert database. Of these 200 VCs, 47 chose to participate in our study (a participation rate of 23.5%). As part of their participation, VCs completed an instrument to evaluate their IT knowledge. VCs were requested to take the quiz themselves and it was suggested they not discuss the questions with anyone. Since VCs always had the option to not participate in the survey and are honorable professionals, there is no apparent reason to doubt their integrity in taking the quiz. All of the participating VCs were partners at their respective firms, and they were not principals or associates. Further, the level of analysis in this work is at an individual VC level and not at the firm level. No two VCs worked for the same firm. Further, it is important to note that data for a VC is at the individual venture funding level and a VC's funding decisions have not been aggregated. Aggregating data on investment decisions or on portfolio performance could hide important nuances in data and invalidate valuable information. Out of 47 VCs, 33 provided detailed information about ventures that sought series A funding from them in 2008. VCs reported this detailed information about ventures to us over the first quarter of 2009. VCs also reported their expected future series B valuations for these ventures.

Expected valuation in the next round is an important judgment call that VCs need to make while investing. Overvaluations erode their governance control and profitability. Hence, VCs have a strong incentive to avoid such overconfidence. Such overconfidence likely shows up because VCs genuinely believe that their assessments are correct. This makes overvaluations an excellent measure for overconfidence. For calculating overvaluation, we also needed an objective measure of series B. We collected the actual valuation data for series B funding, which did not happen until 2010. Series B valuations are largely based on numbers such as market size, patents, revenue growth, the number of users, customer traction, and customer acquisition costs. Ventures by series B have proven their product–market fit and are now looking to scale their proven business model. Ventures need to expand their marketing efforts and need to grow quickly at this stage. At this point, there is a better sense about the return on various marketing efforts and projection numbers are more reliable in general. Consequently, there does not seem to be an apparent reason to believe that series B valuations are systematically inflated. Moreover, the VCs who funded series B were different from the VCs who provided us data in 2009 and did not know the expected series B valuations reported earlier.

We statistically compared 33 VCs who were part of our sample with those who dropped out 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 both groups have similar average age (p-value = 0.39, t-stat = 0.87) and similar average fund size (p-value = 0.77, t-stat = -0.29). We find no evidence to suggest that the VCs who chose to participate are systematically different from the VCs who chose not to participate in any observable way that may threaten the validity of our findings. The 33 VCs offered 215 venture term sheets. The average fund size of the VCs was $122.02 million and VC average valuation of the ventures was $14.67 million.

Key Variables

IT Knowledge

Following best practices in the organizational literature on measurement of knowledge (Ehrlinger et al. 2008; Kruger and Dunning 1999), we used an objective quiz to evaluate the IT knowledge of VCs. This quiz was created through in-depth interviews with the chief technology officers (CTOs) of 11 IT and software companies. These CTOs used the quiz as one of their hiring exams for a total of 57 software professionals in a pretest. Based on the 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 IT knowledge. Accordingly, the number of correct answers on the quiz provides a numerical indicator of the IT knowledge of the person taking the quiz.[2]

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 allocate resources to hiring. They agreed to use the quiz for testing candidates on their IT knowledge and provided the GPA of all applicants who took the quiz. A total of 98 graduating job candidates took the quiz. For these 98 job candidates, we found a positive and significant correlation between GPA and quiz score (ρ = 0.81and p-value < 0.000). Of the 98 candidates, 63 did not have any prior work experience, while the rest had 1 to 3 years of prior work experience. The correlation for these 63 candidates was $\rho = 0.86$ and p-value < 0.000, and the correlation for the remaining 35 candidates was $\rho = 0.78$ and p-value < 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 IT knowledge.

To test the consistency of the measurement of IT knowledge 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 $\frac{2*\rho}{1+\rho}$ where ρ is the correlation between the quiz scores of the two halves. We divided the quiz into two parts based on odd and even question numbers. 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.

Overconfidence

Overconfidence was conceptualized as

$$\frac{100*\left(ExpVal_{ij} - ActVal_j\right)}{ActVal_j}$$

where $ExpVal_{ij}$ is the expected series B funding valuation of VC i for venture j and $ActVal_j$ is the actual series B funding valuation for venture j.

VC Failures

VC failures were defined as the number of VC-funded ventures that defaulted. We considered a company as defaulted if it had filed for bankruptcy or had ceased its operations. This data was provided to us by VCs.

VC Successes

VC successes were measured as the number of successful exits by VCs from ventures which they funded (Shane and Stuart 2002; Tyebjee and Bruno 1984). VCs provided us their past success data.

Stakes

Stakes were operationalized as the amount of funding that a venture requested from the VC. This data was provided by the VCs.

Control Variables

Prior research suggests at least four different categories of factors that are likely to affect VCs' overconfidence in their 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; Gompers et al. 2010; Zacharakis and Meyer 1998).

Environment Controls

VCs' overconfidence 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.

[2]While we cannot share the actual instrument in publication due to its proprietary nature, the instrument was made accessible to the editors and reviewers during the peer review process.

The amount of competition for VCs when choosing to invest in a venture may also influence VCs' overconfidence. The level of competition may raise the bar on the VCs' expectations for venture performance. 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.

Venture Characteristics

The first set of venture characteristics focuses on the characteristics of the founders. Founders' reputation was operationalized by the average number of successful exits (IPOs and acquisitions) led by the founders of a venture. Founders' industry experience was measured by the average of founders' industry experience in years. Founding team project management experience was the average years of experience of managing projects for the founding team. Venture team size was measured as the total number of team members on the venture team.

The second set of venture characteristics focuses on the financial situation of the venture. Projected revenue was operationalized as a venture's assessment of its revenue in three years. Venture market size was measured as the 2008 U.S. market value of the business in dollars.

Additional venture characteristics included venture age and number of patents. 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. Number of patents was measured by the count of patents a venture had applied for at the United States Patent Office. Venture characteristics data was largely provided to us by VCs. In a few cases when certain information was missing, we were able to complete the missing information using VentureXpert and LinkedIn.

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. The VCs' fund size was operationalized as the total funds they raised. To control for VCs' idiosyncratic characteristics, we gathered feedback from founders of ventures that received term sheets from the VCs. Founders reported their assessments of VCs' quality on a scale of 1 to 10, where 10 refers to the highest level and 1 refers to the lowest level. For each VC, we took the average of founders' quality score to calculate VC quality.

VC–Venture Dyad Characteristics

VCs receive a lot of funding requests and they prioritize evaluating deals that come through trusted sources (Shane and Stuart 2002; Tyebjee and Bruno 1984). VCs' trusted sources typically are entrepreneurs with whom they have worked in the past, shared alumni, and other similar associations. Since trusted sources may also affect VCs' overconfidence, we controlled for the extent to which the venture comes to the VC through a trusted referral. Trusted referral was measured if the venture was recommended to the VC from one of its trusted affiliates and VCs shared this data with us. 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. Venture communication skills was measured as the VCs' assessment of the venture's communication skills on a Likert-type scale from 1 to 10 with higher scores representing better communication skills. Venture management capability was similarly measured as the VCs' 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. We also controlled for the distance between a VC and a venture. We calculated distance by identifying longitude and latitude of the main office for each VC and venture, and then calculated distance in miles using the Haversine formula, which takes into account the curvature of the Earth. Descriptive statistics and correlation matrix for all variables are provided in Table 1 and Table 2 respectively.

Empirical Analysis

Model Specification

The general specification of our model is as follows:

$$OverConf_{ij} = \beta_0 + \beta_1 know_i + \beta_2(know_i)^2 + \gamma_1 succ_i + \gamma_2 succ_i \times know_i + \gamma_3 succ_i \times (know_i)^2 + \delta_1 fail_i + \delta_2 fail_i \times know_i + \delta_3 fail_i \times (know_i)^2 + \alpha_1 stakes_j + \alpha_2 stakesj \times know_i + \alpha_3\, stakes_j \times (know_i)^2 + X_i\pi + Y_j\theta + Z_{ij}\psi + \mu_i + \varepsilon_{ij}$$

where $OverConf_{ij}$ is the overconfidence of VC i for venture j, $know_i$ is the IT knowledge of VC i, $succ_i$ is the number of successes for VC i, $fail_i$ is the number of failures for VC i, $stakes_j$ is the amount requested by venture j, X_i is the vector of VC level control variables, Y_j is a vector of venture level control variables, Z_{ij} is a vector of the VC–venture dyad level control variables, μ_i is VC-level unobserved effects, and ε_{ij} is idiosyncratic error.

Table 1. Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Overconfidence (%)	48.4	41.84	-50	150
VC IT knowledge (out of 40)	19.18	5.35	10	28
VC successes	2.62	1.68	1	6
VC failures	7.97	3.68	1	15
Stakes ($Mil)	4.92	1.48	1.5	7.5
VC quality	7.40	1.71	2	10
Team size	3.11	1.16	1	6
Founder reputation	2.40	0.90	0	4
Project management experience	4.09	1.69	0	8
Venture age (months)	13.41	1.60	9	18
Founder experience (years)	9.19	2.64	1	16
Number of patents	1.63	2.47	0	10
Projected revenue ($Mil)	5.52	1.16	2.4	8.4
Dummy soft	0.36	0.48	0	1
Competition	1.53	1.73	0	6
Market size ($Billion)	6.77	4.02	0.16	17
Dummy reference	0.49	0.50	0	1
Communication	6.46	2.75	1	10
Management capability	4.44	1.82	1	10
Distance (miles)	401.30	295.89	25	1753
VC age (Years)	45.90	4.38	38	53
Fund size ($ Million)	127.79	68.37	36	245
Years of experience	8.12	2.94	5	16
VC IT experience	16.82	4.19	10	25

To control for VC-specific unobserved effects, we estimated the model using both a fixed effects model and a random effects model. If unobserved effects are uncorrelated with other independent variables, then a random effect model is preferred over a fixed effects model (Greene 2003). We performed a Hausman test (Greene 2003). The Hausman test was insignificant (χ^2; $p = 0.42$), implying that the VC-level unobserved effects are not correlated with other independent variables. Hence, we use a random effects model to control for VC specific unobserved effects.

Since we have square terms and interaction terms in our model, multicollinearity can be a potential issue. Initial data exploration showed that IT knowledge was highly correlated with its square term. Also, the interactions were highly correlated with the component parts used to define them. The high correlations raises the issue of multicollinearity which, if uncorrected, may lead to inflated standard errors and, in the worst case, inconsistent or unstable estimates (Greene 2003). We used the standard method of mean centering variables before taking their square or forming interaction terms to reduce the correlations to an acceptable level (Gelman and Hill 2007; Jaccard and Turrisi 2003). As a diagnostic check for multicollinearity, we calculated the variance inflation factors (VIF) for each variable (Greene 2003); the maximum value of VIF across all models is 5.26, which is below the generally accepted threshold of 10 (Belsley et al. 2004).

Results

The detailed results of our analysis are presented in Table 3. Model 1 contains control variables only. Model 2 reports the results when we add focal independent variables to the analysis. Wald test indicates that coefficients of focal independent variables are not simultaneously equal to zero (χ^2, $p <$

Table 2. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Overconfidence	1											
2	VC IT knowledge	0.10	1										
3	VC successes	0.13	0.13	1									
4	VC failures	-0.55	-0.33	0.35	1								
5	Stakes	-0.34	-0.10	-0.18	0.04	1							
6	VC quality	-0.20	0.02	-0.33	-0.15	0.14	1						
7	Team size	0.19	0.00	0.10	0.02	-0.14	0.07	1					
8	Founder reputation	-0.04	-0.04	-0.03	0.00	0.22	0.07	-0.057	1				
9	Project management experience	0.13	0.03	-0.01	0.00	0.12	0.13	0.18	0.09	1			
10	Venture age	0.05	-0.03	0.03	-0.08	0.11	0.05	-0.01	0.11	0.07	1		
11	Founder experience	0.08	0.05	-0.09	-0.02	0.17	0.14	0.07	0.23	0.19	0.14	1	
12	Number of patents	0.21	0.10	0.05	-0.03	-0.22	0.01	0.09	-0.14	0.16	-0.09	-0.06	1
13	Projected revenue	-0.03	0.02	-0.08	-0.04	0.13	0.01	0.06	0.14	0.00	0.17	0.14	-0.05
14	Dummy soft	0.09	0.18	-0.03	-0.14	0.02	0.03	0.00	-0.05	0.04	-0.01	0.07	0.01
15	Competition	0.00	-0.08	-0.07	-0.01	-0.05	-0.01	-0.09	-0.07	-0.14	-0.02	-0.09	0.04
16	Market size	0.19	-0.02	0.15	0.03	-0.22	-0.10	0.10	-0.17	0.00	-0.04	-0.02	0.15
17	Dummy reference	0.04	0.05	-0.09	-0.01	-0.05	0.07	0.00	0.11	0.10	-0.12	0.07	0.05
18	Communication	0.02	-0.08	0.08	0.04	0.22	0.00	0.06	0.10	0.26	-0.05	-0.01	0.04
19	Management capability	0.22	-0.01	0.06	0.01	-0.09	-0.22	-0.02	-0.15	0.00	0.07	-0.02	0.11
20	Distance	-0.10	0.02	0.05	0.09	0.14	0.01	-0.04	0.07	-0.06	0.07	0.08	-0.21
21	VC age	0.24	-0.02	0.18	-0.24	-0.11	0.12	0.08	-0.04	0.06	0.01	-0.06	0.07
22	Fund size	-0.33	0.40	-0.33	-0.07	0.25	0.30	-0.07	0.12	0.15	0.02	0.13	-0.05
23	Years of experience	0.12	-0.17	0.09	0.02	-0.05	-0.06	-0.01	0.04	-0.13	-0.06	0.07	-0.08
24	VC IT experience	-0.12	-0.56	-0.13	0.04	0.15	0.02	-0.07	0.12	0.00	0.09	-0.11	-0.10

		13	14	15	16	17	18	19	20	21	22	23	24
13	Projected revenue	1											
14	Dummy soft	0.07	1										
15	Competition	0.11	0.00	1									
16	Market size	0.08	-0.06	0.10	1								
17	Dummy reference	-0.04	-0.03	-0.08	-0.05	1							
18	Communication	0.04	0.11	0.03	-0.13	0.00	1						
19	Management capability	-0.01	-0.01	0.01	0.10	-0.07	0.06	1					
20	Distance	0.01	-0.09	0.09	-0.16	0.07	0.08	-0.03	1				
21	VC age	-0.06	0.01	-0.06	0.01	-0.17	0.01	0.01	0.04	1			
22	Fund size	0.01	0.04	-0.01	-0.13	0.13	-0.08	-0.14	0.12	-0.08	1		
23	Years of experience	-0.15	-0.02	0.08	-0.15	-0.08	0.00	-0.02	0.03	0.09	-0.25	1	
24	VC IT experience	-0.01	-0.08	0.03	0.02	-0.06	0.08	-0.08	-0.06	0.23	-0.24	0.06	1

Table 3. Overconfidence Models

	Random Effects Models								
	Model: Only Controls	Model: No-interaction model	Model: Interactions of successes with VC IT knowledge		Model: Interactions of failures with VC IT knowledge		Model: Interactions of stakes with VC IT knowledge		Model
	M1	M2	M3a: Interaction with linear term	M3b: Interaction with linear term and square term	M4a: Interaction with linear term	M4b: Interaction with linear term and square term	M5a: Interaction with linear term	M5b: Interaction with linear term and square term	Complete M6
	Dependent variable: VCs' overconfidence								
VC IT Knowledge		-1.9940***	-2.3070***	-1.8875**	-2.0001***	-2.0945**	-2.0890***	-2.0524***	-2.1415**
		(0.6965)	(0.7731)	(0.7403)	(0.7115)	(0.9829)	(0.6553)	(0.6624)	(0.9225)
VC successes		4.8486	5.0281	0.2819	5.2192	5.3496	3.8714	3.5309	0.6424
		(3.2869)	(3.3022)	(4.7314)	(3.3369)	(3.4537)	(3.2018)	(3.1130)	(4.8802)
VC failures		-7.7879***	-7.8803***	-7.5938***	-7.7880***	-7.7500***	-7.6304***	-7.5272***	-6.9134***
		(0.8752)	(0.8737)	(1.0002)	(0.8506)	(0.9766)	(0.8803)	(0.9150)	(1.2844)
Stakes		-3.6202***	-3.5489***	-3.3900***	-3.5534***	-3.5426***	-3.8966***	-3.4035***	-3.5745***
		(1.0028)	(0.9874)	(0.9897)	(1.0158)	(1.0063)	(0.5793)	(1.0328)	(0.9937)
(VC IT Knowledge)^2		0.5948***	0.6142***	0.6100***	0.5482***	0.5427***	0.5951***	0.6011***	0.5131***
		(0.1598)	(0.1533)	(0.1287)	(0.1774)	(0.1898)	(0.1473)	(0.1431)	(0.1638)
VC IT Knowledge × VC successes			0.3048	0.2311					0.0368
			(0.3201)	(0.2312)					(0.2497)
(VC IT Knowledge)^2 × VC successes				0.1422**					0.1195*
				(0.0633)					(0.0700)
VC IT Knowledge × VC failures					-0.168	-0.1845			-0.3249
					(0.2110)	(0.2490)			(0.2348)
(VC IT Knowledge)^2 × VC failures						-0.0051			-0.0259
						(0.0310)			(0.0305)
VC IT Knowledge × stakes							-0.5096***	-0.5557***	-0.5003***
							(0.1043)	(0.1218)	(0.1385)
(VC IT Knowledge)^2 × stakes								-0.0175	-0.0071
								(0.0247)	(0.0267)
VC Quality	-2.508	-1.2523	-1.618	-0.5491	-0.773	-0.7525	-1.2893	-1.4273	0.0721
	(3.2656)	(1.9184)	(2.0397)	(1.9050)	(2.0248)	(2.0255)	(1.8478)	(1.8459)	(1.8616)
Team size	0.9945	1.2059**	1.2018**	1.1768*	1.2022*	1.1908*	1.1891**	1.3139**	1.3416**
	(0.7154)	(0.6076)	(0.6073)	(0.6070)	(0.6153)	(0.6202)	(0.5886)	(0.5901)	(0.5940)
Founder reputation	1.9050*	1.8535*	1.8335*	1.8171*	1.8494*	1.8443*	2.0307**	2.1620**	2.1607**
	(1.0056)	(0.9877)	(0.9867)	(0.9829)	(0.9852)	(0.9934)	(0.9177)	(0.9326)	(0.9362)
Project management Experience	1.5759**	1.7184***	1.7491***	1.6854***	1.6989***	1.6949***	1.5893***	1.6112***	1.6568***
	(0.7008)	(0.5547)	(0.5630)	(0.5717)	(0.5600)	(0.5633)	(0.5143)	(0.5206)	(0.5365)
Venture age	0.2522	0.5288	0.5278	0.4819	0.5069	0.5008	0.584	0.6333	0.6105
	(0.5437)	(0.4644)	(0.4683)	(0.4730)	(0.4603)	(0.4610)	(0.4193)	(0.4400)	(0.4481)
Founder experience	1.8981***	2.0773***	2.0820***	2.0550***	2.0852***	2.0890***	1.8208***	1.7341***	1.7345***
	(0.3251)	(0.3103)	(0.3113)	(0.3043)	(0.3088)	(0.3083)	(0.3127)	(0.3343)	(0.3405)
Number of patents	0.2363	0.3334	0.3308	0.3353	0.3213	0.3157	0.2762	0.3394	0.3399
	(0.4414)	(0.3875)	(0.3911)	(0.3947)	(0.3871)	(0.3908)	(0.4253)	(0.4254)	(0.4304)

Table 3. Overconfidence Models (Continued)

	Random Effects Models								
	Model: Only Controls	Model: No-interaction model	Model: Interactions of successes with VC IT knowledge		Model: Interactions of failures with VC IT knowledge		Model: Interactions of stakes with VC IT knowledge		Model
	M1	M2	M3a: Interaction with linear term	M3b: Interaction with linear term and square term	M4a: Interaction with linear term	M4b: Interaction with linear term and square term	M5a: Interaction with linear term	M5b: Interaction with linear term and square term	Complete M6
	Dependent Variable: VCs' Overconfidence								
Projected revenue	0.1296	0.1059	0.1146	0.1695	0.1197	0.1286	0.2863	0.1933	0.2403
	(0.7703)	(0.7341)	(0.7420)	(0.7453)	(0.7382)	(0.7391)	(0.7500)	(0.7500)	(0.7646)
Dummy soft	1.8308	1.8165	1.7802	1.6994	1.7771	1.7814	2.0957	2.3736	2.2016
	(1.9587)	(1.5524)	(1.5641)	(1.5663)	(1.5565)	(1.5709)	(1.5464)	(1.5417)	(1.5718)
Competition	0.9641*	0.8971***	0.9132***	0.9227***	0.9181***	0.9226***	0.6920**	0.6194**	0.6916**
	(0.5414)	(0.3121)	(0.3122)	(0.3128)	(0.3125)	(0.3141)	(0.2943)	(0.3143)	(0.3113)
Market size	0.9652**	0.4353*	0.4374*	0.4459*	0.4470*	0.4491*	0.4348*	0.4254*	0.4647**
	(0.4161)	(0.2318)	(0.2321)	(0.2385)	(0.2359)	(0.2378)	(0.2249)	(0.2215)	(0.2307)
Dummy reference	4.2389***	3.0985**	3.0752**	2.8693**	3.0298**	3.0152**	3.0439***	3.5236***	3.1780***
	(1.5693)	(1.2729)	(1.2957)	(1.2977)	(1.2800)	(1.2902)	(1.1473)	(1.2593)	(1.2265)
Communication	0.1119	0.471	0.4631	0.4507	0.4658	0.4661	0.4421	0.4471	0.4349
	(0.3412)	(0.3509)	(0.3520)	(0.3525)	(0.3526)	(0.3524)	(0.3272)	(0.3316)	(0.3363)
Management capability	0.8173**	0.9765**	0.9862**	0.9907**	0.9549**	0.9469**	0.8909**	1.0199***	0.9972***
	(0.4127)	(0.4236)	(0.4264)	(0.4159)	(0.4257)	(0.4214)	(0.3767)	(0.3793)	(0.3816)
Distance	-0.0042	-0.0029	-0.003	-0.0031	-0.003	-0.003	-0.0024	-0.0019	-0.002
	(0.0027)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0022)	(0.0022)
VC age	3.0927**	0.6435	0.7085	0.3747	0.435	0.4229	0.6875	0.6761	0.1002
	(1.2274)	(0.9741)	(0.9850)	(1.0615)	(1.0736)	(1.0686)	(0.9808)	(0.9703)	(1.0994)
Fund size	-0.1708**	-0.0465	-0.0304	-0.022	-0.0418	-0.0397	-0.0317	-0.0317	-0.0077
	(0.0776)	(0.0626)	(0.0682)	(0.0708)	(0.0640)	(0.0660)	(0.0621)	(0.0618)	(0.0693)
VC IT experience	-2.9769	-1.8255	-1.8617	-1.1605	-1.6989	-1.735	-1.8201	-1.7503	-1.1406
	(2.4692)	(1.9647)	(1.9777)	(1.0368)	(1.9942)	(1.0754)	(1.9675)	(1.9627)	(1.0566)
(VC IT experience)^2	0.3289	0.1156	0.049	0.1348	0.2033	0.2112	0.0994	0.094	0.3142
	(0.3060)	(0.2208)	(0.2471)	(0.1908)	(0.2450)	(0.2568)	(0.2138)	(0.2108)	(0.2284)
Years of experience	1.3117	-1.8937*	-2.2114**	-1.4483	-1.8234*	-1.8358*	-2.0303**	-2.0560**	-1.4535
	(1.5634)	(1.0620)	(1.0377)	(1.0008)	(1.0952)	(1.0841)	(0.9874)	(0.9382)	(0.9368)
Constant	-124.6986**	43.7967	57.3641	52.3072	-15.6972	-15.8551	26.0264	26.3505	-22.37
	(57.9865)	(50.1077)	(51.3307)	(57.6817)	(47.0001)	(47.2180)	(49.1328)	(48.3838)	(50.6541)
Adjusted R^2	0.3696	0.8089	0.8098	0.8285	0.808	0.8072	0.8283	0.8277	0.8371
N	215	215	215	215	215	215	215	215	215

All the reported models are random effects models. Model 1 presents results of model with only control variables; model M2 (no-interaction model) adds focal independent variables in addition to control variables; model M3a adds interaction of successes with VCs' IT knowledge to the no-interaction model; model M3b adds interaction of successes with square of VCs' IT knowledge to the model M3a; model M4a adds interaction of failures with VCs' IT knowledge to the no-interaction model; model M4b adds interaction of failures with square of VCs' IT knowledge to the model M4a; model M5a adds interaction of stakes with VCs' IT knowledge to the no-interaction model; model M5b adds interaction of stakes with square of VCs' IT knowledge to the model M5a; model M6 is complete model with all interaction terms.

Notes: Robust standard errors are in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

0.01) which suggests that focal independent variables have a significant influence on overconfidence. Henceforth, we will refer to model 2 as the no-interactions model. The subsequent models report results where we add interaction terms to the no-interactions model. Models M3a, M4a, and M5a add interactions of VCs' IT knowledge with successes, failures and stakes respectively. Models M3b, M4b, and M5b add interactions of both VCs' IT knowledge and square of VCs' IT knowledge with successes, failures, and stakes, respectively. Model M6 is the complete model and adds all the interaction terms simultaneously.

Hypothesis 1 Result: Effect of IT Knowledge on Overconfidence

Consistent with hypothesis 1, we find that IT knowledge has a curvilinear relationship with over-confidence. The coefficient of IT knowledge is negative and statistically significant (-2.1415, p-value < 0.05) whereas the coefficient of square of IT knowledge is positive and statistically significant (0.5131, p-value < 0.01). The positive and significant value of the square term indicates that the relationship between IT knowledge and overconfidence is not linear. Figure 1 plots the predicted value of overconfidence at different values of IT knowledge keeping all other independent variables at their mean value. Figure 1 shows that the predicted value of overconfidence is highest at minimum value of IT knowledge. As IT knowledge increases from its minimum value, overconfidence first decreases and reaches a minimum point when IT knowledge is moderate. Overconfidence subsequently increases with increase in VCs' IT knowledge. This means that VCs with high and low IT knowledge will be more overconfident than VCs with a moderate level of IT knowledge.

Hypothesis 2 Result

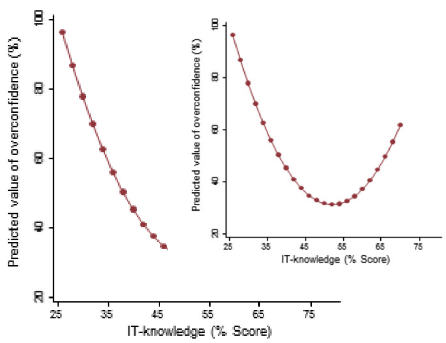
Effect of VC successes on overconfidence: In model 6, $succ_i$, $succ_i \times know_i$, and $succ_i \times know_i^2$ together represent the influence of successes in predicting overconfidence. The coefficient of interaction of square of IT knowledge with successes is positive and statistically significant (0.1195, p-value < 0.1), which indicates that the marginal effect of successes has a non-linear relationship with IT knowledge (Aiken and West 1991). However, the conclusion about the marginal effect for successes cannot be made from the table alone (Davidson and MacKinnon 1993). The mean of marginal effect of successes is $\gamma_1 + \gamma_2 know_i + \gamma_3(know_i)^2$ and the standard error of the marginal effect is $\Sigma_{j,k=1}^{3} \alpha_j \alpha_k COV(\gamma_j, \gamma_k)$, where $\alpha_1 = 1$, $\alpha_2 = know_i$, and $\alpha_3 = know_i^2$. As evident from these equations, the mean and the standard error of marginal effect of successes depend on value of the VCs' IT knowledge.

To correctly interpret the statistical significance of the marginal effect of successes across varying levels of the moderating variable, we plot the mean value of marginal effect of the successes on overconfidence along with the confidence intervals at different values of the VCs' IT knowledge in Figure 2. In Figure 2, the confidence intervals intersect the x-axis for the mid-range of knowledge values which indicates that the marginal effect of successes is insignificant for moderate values of VCs' IT knowledge. Nevertheless, the confidence intervals are above zero on both the left side and the right side of Figure 2, which indicates that the marginal effect of successes is positively significant at both high and low values of the VCs' IT knowledge. Further, the marginal effect of success on overconfidence initially decreases with an increase in VCs' IT knowledge and reaches a minimum point when VCs' IT knowledge is at the same level at which overconfidence was at its minimum. Subsequently, the marginal effect of successes increases with an increase in IT knowledge. In conclusion, the biasing positive effect of successes on overconfidence is higher at the extreme ends of the IT knowledge continuum and the effect decreases and subsequently becomes insignificant as we move toward the midrange of VCs' IT knowledge.

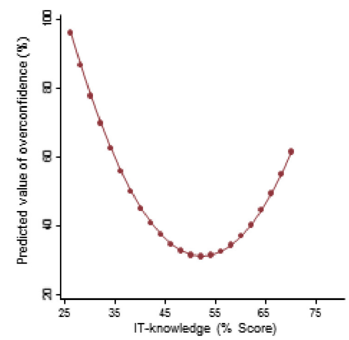
Effect of VC failures on overconfidence: In model 6, $fail_i$, $fail_i \times know_i^2$, and $fail_i \times know_i^2$ together represent the influence of failures in predicting overconfidence. Both the coefficient of interaction of IT knowledge with failures and square of IT knowledge with failures are insignificant, which suggests that IT knowledge does not significantly moderate the influence of failures on overconfidence (Aiken and West 1991).

Although the above result indicates that IT knowledge does not moderate the influence of failures on overconfidence, it does not imply that failures have no significant influence on overconfidence. To correctly interpret the statistical significance of marginal effect of failures across varying levels of interacting variables, we plot the mean value of marginal effect of the failures on overconfidence along with the confidence intervals at different values of the VCs' IT knowledge in Figure 3. In Figure 3, the confidence intervals are always below zero, which indicates that failures have a significant negative effect on overconfidence for all values of VCs' IT knowledge. In conclusion, failures have a significant negative effect on overconfidence but the effect does not change significantly with the VCs' IT knowledge.

Successes are consistent with the moderation effect theorized in hypothesis 2, whereas failures do not show such a moderation effect. To sum up, hypothesis 2 is supported for successes but not for failures.

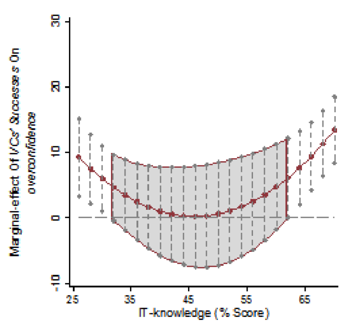


Based on Model 2 (Model with square VCs' IT knowledge and no interaction terms)

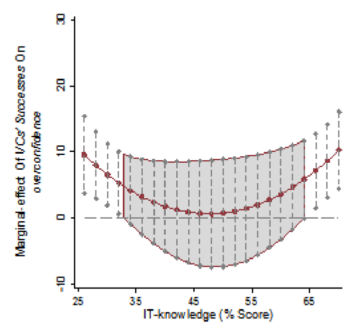


Based on Model 6 (Complete model)

Figure 1. Predicted Value of Overconfidence (%) at Different Values of VCs' KIT Knowledge



Based on Model 4b (Model with interaction of successes with VCs' IT knowledge, interaction of successes with square VCs' IT knowledge, and no other interaction term)



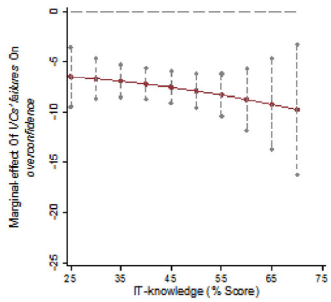
Based on Model 6 (Complete model)

Solid line represents mean value of the marginal effect and dashed vertical lines represent 90% confidence interval (CI). **The gray regions represent regions where marginal effect is significant (i.e., where CI intersects $x = 0$ line).**

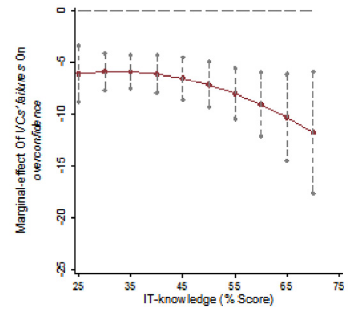
Figure 2. Marginal Effect of Successes on Overconfidence at Different Values of VCs' IT Knowledge

Hypothesis 3 Results: Effect of Stakes on Overconfidence

In model 6, $stake_j$, $stake_j \times know_i$ and $stake_j \times know_i^2$ together represent the influence of stakes in predicting overconfidence. The coefficient of interaction of square of IT knowledge with stakes is insignificant. This result indicates that the marginal effect of IT knowledge will not have a significant curvilinear relationship with VCs' IT knowledge. However, the conclusion about the marginal effect of stakes cannot be made from the table alone (Davidson and MacKinnon 1993). To correctly interpret whether the marginal effect is statistically significant across varying levels of VCs' IT knowledge, we plot the mean value of marginal effect of the stakes on overvaluation along with the 90 percent confidence intervals at different values of VCs' IT knowledge in Figure 4. In Figure 4, the confidence intervals intersect the x-axis at low values of VCs' IT knowledge, which indicates that the marginal effect is not statistically different from zero at low values of the VCs' IT knowledge. Nevertheless, the confidence intervals are below zero at higher values of the VCs' IT knowledge, which indicates that the marginal effect is negatively significant at the higher values of the VCs' IT knowledge. These results provide support for hypothesis 3.



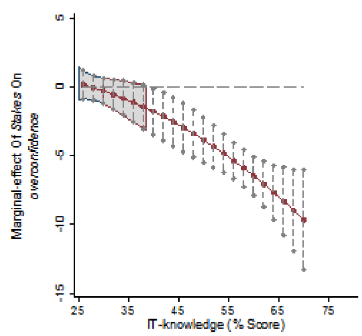
Based on Model 5b (Model with interaction of failures with VCs' IT knowledge, interaction of failures with square of VCs' IT knowledge, and no other interactions)



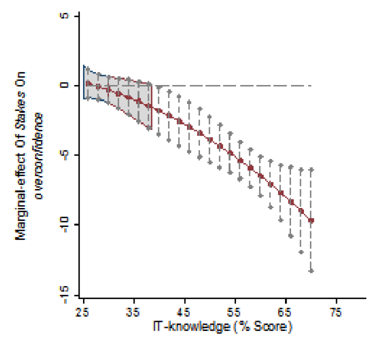
Based on Model 6 (Complete model)

Solid line represents mean value of the marginal effect and dashed vertical lines represent 90% confidence interval (CI).

Figure 3. Marginal Effect of Failures on Overconfidence at Different Values of VCs' IT Knowledge



Based on Model 2b (Model with interaction of stakes with VCs' IT knowledge, interaction of stake with square of VCs' IT knowledge, and no other interactions)



Based on Model 6 (Complete model)

Solid line represents mean value of the marginal effect and dashed vertical lines represent 90% confidence interval (CI). **The gray regions represent regions where marginal effect is insignificant (i.e., where CI intersects $x = 0$ line).**

Figure 4. Marginal Effect of Stakes on Overconfidence at Different Values of VCs' IT Knowledge

Effect of Stakes on Overconfidence: Results Summary

We find support for hypotheses 1, and 3, but found only partial support for hypothesis 2. The results indicate that VCs with high and low levels of IT knowledge are more likely to be overconfident than VCs with a moderate level of IT knowledge. Our results also suggest that IT knowledge initially reduces the biasing effects of successes on overconfidence; however, when IT knowledge increases beyond a certain level, it increases the effect of successes on overconfidence. The failures have a negative effect on overconfidence but the effect does not change with VCs' IT knowledge. Also, stakes have a negative effect on overconfidence and this effect increases with VCs' IT knowledge.

Robustness Checks: Quiz Reliability

Earlier, we reported the quiz reliability using the split-half method, which calculated quiz reliability based on the correlation between scores on the even-half and the odd-half of the quiz. As an additional robustness check, we estimated models using scores on the even-half and the odd-half of the quiz. The results using scores on the even-half, the odd-half, and the complete quiz are quantitatively similar, which corroborates the reliability of the quiz score. The result of this analysis is reported in models R1 and R2 in Table 4.

Curvilinear effect of VC experience: There is a possibility that general business knowledge may have a nonlinear effect on overconfidence. We use experience[3] as a proxy for general business knowledge and control for this potential nonlinear effect in an additional robustness check. The results of the analysis are reported in model R3 in Table 4. The results are qualitatively similar even after controlling for curvilinear effects of VCs' general experience.

Selection bias: We have overconfidence data for only ventures that received funding from VCs. This can lead to sample selection as VCs may systematically fund certain ventures over others. We followed the standard method of Heckman two step models to account for the selection bias (Heckman1979). In the first stage of the analysis, a probit regression was used to estimate the likelihood of a venture receiving funding using the sample of the ventures that VCs invited to give presentations. The results of step 1 are reported in model R4 in Table 4. Estimates from step 1 are then used to obtain a Heckman's selection correction term. In step 2, we inserted the correction term into overconfidence equation and reestimated the model. The results remain qualitatively similar even after controlling for selection bias and are reported in model R5 in Table 4.

Alternative measure for overconfidence: In our analysis, we used overvaluation as a measure for overconfidence. A concern with this measure could be that series B valuations could be biased, especially if the same VCs funded both series A and series B. However, this is not a problem in our dataset, since no VC funded both rounds in our sample. Any such potential bias should only add noise to the data and should not systematically affect the results. However, as a robustness check, instead of using overvaluation, we used expected valuations as a measure of overconfidence, and the results were qualitatively the same. The results of this analysis are reported in model R6 in Table 4.

Robustness check for overfitting: To allay concerns with overfitting we repeated the analyses using a simple model containing only the key explanatory variables and interactions. These results are shown in model R7 in Table 4. The predicted relationships still hold in this simple model, suggesting that overfitting should not be a concern.

Robustness check for VC heterogeneity: Based on a Hausman test, we used a random effects model to control for unobserved heterogeneity across VCs. As an additional robustness check, we now report the results of a VC fixed effects model as well. The results of the VC fixed effects model are qualitatively similar to the results reported earlier and are reported in model R8 in Table 4.

Conclusion and Discussion

Our research contributes to the literature on how IT knowledge affects overconfidence in decisions, particularly in IT investments, in several ways. First, we propose and empirically test the U-shaped relationship between IT knowledge and VC overconfidence. To the best of our knowledge, this nonlinear relationship has not been explored so far, and it explains the contradictory findings reported in the broader decision-making literature regarding the relationship between knowledge and overconfidence. Our work cautions researchers from defining *experts* as individuals who know more than others irrespective of their specific place on the knowledge continuum as there may be nonlinear effects of expertise.

Second, we point out that IT knowledge may moderate the effect of past successes and failures on VC overconfidence. As far as we know, how knowledge may change the effect of successes and failures on overconfidence has not been studied before. While findings support the moderation effect of IT knowledge for successes, they do not support the moderation effect of IT knowledge for failures. Perhaps future research should examine why failures reduce overconfidence irrespective of IT knowledge.

Third, we suggest that IT knowledge strengthens the debiasing effect of stakes on overconfidence, and find support for it in the data. That is, without IT knowledge, VCs are not able to respond to higher stakes decisions requiring more accurate venture assessments. VCs' judgments are less overconfident in the face of higher stakes only when they possess higher levels of IT knowledge, and that emphasizes the practical relevance of IT knowledge.

Fourth, we examined real-life funding decisions of VCs in the IT domain worth millions of dollars and, thus, our research hypotheses were subjected to strict falsifiability. Importantly, we measure overconfidence at a point where it matters practically: individual firm valuation judgments. Firm valua-

[3]We thank William Kettinger and the anonymous review team for suggesting we use experience as a proxy for general business knowledge.

Table 4. Robustness Check

	Quiz reliability		VC experience	Selection bias		Over-confidence measure	Overfitting	VC heterogeneity
	R1: Even half	R2: Odd Half	R3: Model with curvilinear effect of VC experience	R4: Probit model for funding decision	R5: Over confidence model with selection bias correction	R6: Model with Expected series B valuation as dependent variable	R7: Model with focal independent variables only	R8: Fixed effects model
VC IT Knowledge	-2.2485***	-2.3560**	-1.5457*	-0.0116	-2.1294**	-0.1771**	-1.1202**	
	(0.7894)	(0.9286)	(0.9032)	(0.0233)	(0.9399)	(0.0843)	[0.4814]	
VC successes	2.3888	0.6572	-0.327	0.1014	0.2123	-0.2646	-1.5477	
	(4.1713)	(5.2502)	(3.9006)	(0.0769)	(4.8977)	(0.3129)	(4.2196)	
VC failures	-7.0555***	-6.4798***	-6.4221***	-0.0211	-7.0584***	-0.5108***	-8.1024***	
	(1.1406)	(1.4156)	(1.3724)	(0.0284)	(1.2347)	(0.1068)	(1.0463)	
Stakes	-3.0678***	-4.3652***	-5.4770***	0.3729***	-5.4960***	-0.6019*	-2.1362**	-3.1901***
	(0.8681)	(1.1284)	(1.4882)	(0.0732)	(2.1122)	(0.3154)	(0.8472)	(0.9495)
(VC IT Knowledge)²	0.4337***	0.5066***	0.5418***	0.0035	0.4909***	0.0700***	0.6210***	
	(0.1322)	(0.1737)	(0.1610)	(0.0034)	(0.1692)	(0.0169)	(0.1273)	
VC IT Knowledge × VC successes	0.0561	0.0564	0.0891	0.0101	-0.0051	0.0147	-0.1035	
	(0.2952)	(0.3239)	(0.2735)	(0.0088)	(0.2527)	(0.0339)	(0.2546)	
(VC IT Knowledge)² × VC successes	0.1279*	0.1396*	0.1372**	-0.0024	0.1293*	0.0212***	0.1439*	
	(0.0673)	(0.0815)	(0.0641)	(0.0016)	(0.0714)	(0.0080)	(0.0747)	
VC IT Knowledge × VC failures	-0.2606	-0.4833	-0.2913	0.0047	-0.3341	-0.0016	0.0994	
	(0.1904)	(0.2967)	(0.2446)	(0.0072)	(0.2384)	(0.0295)	(0.2050)	
(VC IT Knowledge)² × VC failures	-0.031	-0.0383	-0.0277	0.0000	-0.0214	0.0002	0.0286	
	(0.0275)	(0.0397)	(0.0333)	(0.0010)	(0.0299)	(0.0032)	(0.0324)	
VC IT Knowledge × stakes	-0.5397***	-0.4590***	-0.3943**	-0.0056	-0.4765***	-0.0632**	-0.6775***	-0.5079***
	(0.1098)	(0.1442)	(0.1909)	(0.0083)	(0.1446)	(0.0313)	(0.1136)	(0.1311)
(VC IT Knowledge)² × stakes	-0.0179	0.0068	0.0259	-0.0040***	0.0143	0.0000	-0.0282	-0.0116
	(0.0180)	(0.0300)	(0.0371)	(0.0015)	(0.0366)	(0.0063)	(0.0241)	(0.0259)
VC Quality	-0.2434	-0.1859	-1.0336	-0.0627	0.3397	-0.3682		
	(2.1746)	(1.8090)	(1.7517)	(0.0456)	(1.9540)	(0.2855)		
Team size	1.5701**	1.4778**	2.8408***	0.1820***	0.2624	-0.076		1.0847*
	(0.6127)	(0.6063)	(0.8434)	(0.0497)	(0.9952)	(0.1928)		(0.5913)
Founder reputation	2.2850**	2.3099**	3.1207**	-0.0462	2.3094**	0.1232		1.9058**
	(0.9836)	(0.9325)	(1.3259)	(0.0717)	(0.9321)	(0.2597)		(0.8868)
Project management experience	1.7037***	1.9290***	2.9672***	0.2154***	0.4708	0.3207**		1.3801**
	(0.5202)	(0.5562)	(0.7009)	(0.0405)	(1.0247)	(0.1505)		(0.5273)
Venture age	0.5402	0.8624*	1.225	0.0298	0.4079	0.0539		0.4359
	(0.4642)	(0.5040)	(0.9013)	(0.0376)	(0.4580)	(0.1201)		(0.4065)
Founder experience	1.5755***	1.7720***	1.1447**	0.0334	1.5783***	0.0457		1.8678***
	(0.3683)	(0.3537)	(0.5541)	(0.0234)	(0.3288)	(0.0792)		(0.3031)
Number of patents	0.4696	0.3757	1.1295**	0.0713**	-0.0753	0.0115		0.2468
	(0.4309)	(0.4428)	(0.5744)	(0.0301)	(0.4894)	(0.0758)		(0.4238)
Projected revenue	0.1174	0.1913	-0.123	0.0980*	-0.1887	-0.3609*		0.3551
	(0.7604)	(0.7775)	(0.8775)	(0.0536)	(0.7704)	(0.1911)		(0.7484)
Dummy soft	2.5632	2.0627	3.0173	-0.2757**	3.4940*	0.2614		1.9918
	(1.6008)	(1.5367)	(2.1731)	(0.1236)	(1.9208)	(0.4691)		(1.5963)

Table 4. Robustness Check (Continued)								
	Quiz reliability		VC experience	Selection bias		Over-confidence measure	Overfitting	VC heterogeneity
	R1: Even half	R2: Odd Half	R3: Model with curvilinear effect of VC experience	R4: Probit model for funding decision	R5: Over confidence model with selection bias correction	R6: Model with Expected series B valuation as dependent variable	R7: Model with focal independent variables only	R8: Fixed effects model
Competition	0.6291**	0.7118**	0.7251*	0.021	0.6643**	0.0009		0.7733**
	(0.3120)	(0.3107)	(0.4024)	(0.0339)	(0.3198)	(0.1194)		(0.3048)
Market size	0.4395**	0.4997**	0.4045	0.0248	0.3244	0.1016*		0.4103
	(0.2200)	(0.2291)	(0.2546)	(0.0171)	(0.2638)	(0.0522)		(0.2453)
Dummy reference	4.0504***	2.7853**	4.4687**	0.5776***	-0.1616	0.1273		2.8289**
	(1.3010)	(1.2278)	(1.8227)	(0.1240)	(3.0056)	(0.3792)		(1.2232)
Communication	0.4062	0.4706	0.3663	0.0334	0.2489	-0.0035		0.4254
	(0.3310)	(0.3553)	(0.4010)	(0.0217)	(0.3810)	(0.0725)		(0.3198)
Management capability	1.1905***	1.0210***	1.6720**	0.0709**	0.528	0.2708*		0.8229**
	(0.4126)	(0.3828)	(0.6890)	(0.0310)	(0.4953)	(0.1435)		(0.3802)
Distance	-0.0014	-0.0017	0.002	-0.0011***	0.004	0.0007		-0.0027
	(0.0021)	(0.0023)	(0.0033)	(0.0002)	(0.0056)	(0.0006)		(0.0022)
VC age	-0.0015	0.2452	0.0699	0.0093	0.0641	0.091		
	(0.9708)	(1.2029)	(1.0302)	(0.0175)	(1.1102)	(0.1030)		
Fund size	-0.014	-0.0065	-0.0166	0.0001	-0.0091	0.0015		
	(0.0685)	(0.0643)	(0.0628)	(0.0013)	(0.0703)	(0.0071)		
VC IT experience	-0.9961	-1.4608	-0.7034	-0.006	-1.2016	-0.0298		
	(1.0646)	(1.0305)	(0.9344)	(0.0196)	(1.0733)	(0.0966)		
(VC IT experience)^2	0.3155	0.3985	0.2697	-0.0103	0.3575	-0.0175		
	(0.2135)	(0.2502)	(0.1985)	(0.0156)	(0.2413)	(0.0281)		
Years of experience	-1.4194	-1.3483	-1.3425	0.0036	-1.5143	-0.5834***		
	(1.0112)	(0.9068)	(1.3212)	(0.0274)	(0.9649)	(0.1272)		
(Years of experience)^2			0.0383					
			(0.3620)					
Selection bias correction factor (Inverse mills ratio)					-9.3193			
					(7.5128)			
Constant	-11.6567	-36.1646	-43.6336	-2.9047***	3.3274	19.4889***	30.0675***	-2.3337
	(46.5404)	(51.7457)	(43.4991)	(0.9543)	(55.0396)	(3.8679)	(5.5641)	(8.5189)
Adjusted R^2/Log likelihood	0.8452	0.8549	0.8607	-299.7398	0.8612	0.687	0.7754	0.576
N	215	215	215	689	215	215	215	215

All the reported models except model R8 are random effects models. Model R8 is a fixed effects model. All models present results for robustness checks pertaining to (1) quiz reliability (R1 and R2), (2) VC experience (R3), (3) selection bias (R4 and R5), (4) the measure of overconfidence (R6), (5) overfitting (R7), and (6) VC heterogeneity (R8). The dependent variable in all models except models R4 and R6 is VC overconfidence. The dependent variables in models R4 and R6 are the funding decision and the expected series B valuation respectively.

Notes: Robust standard errors are in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

tion in the next round is an important judgment call that VCs need to make while investing as overvaluations may seriously hurt their governance control and profitability.

An important strength of this research lies in our use of unique data collected specifically for the purpose of this study in a highly consequential domain of IT investments. Our onerous data collection effort has enabled us to create an extensive list of control variables to rule out potential confounding effects. The reliability of our measure of IT knowledge was tested by using the split half method, and the robustness of the results gives us confidence in the findings we report for the effect of IT knowledge.

Our work sheds light on the debate among the venture capital community on the role of IT knowledge for assessing IT investments. Most VCs investing in IT ventures do not have formal education in IT and, by and large, have worked in one of three professions: as lawyers, as investment bankers, or as management consultants. Our work shows that VCs with low IT knowledge are not only overconfident in their decisions, but also fail to correct their tendency to be overconfident even when strongly motivated to do so, for example, when making big funding decisions. Even though VCs do not have to write any code for the technical product they fund, low IT knowledge is a disadvantage compared to even moderate IT knowledge. Moreover, moderate IT knowledge has an added benefit of helping VCs resist the biasing effects of past successes. In fact, VCs with moderate IT knowledge are less likely to be overconfident following successful funding decisions compared to both VCs with low and high IT knowledge.

An implication for the venture capital industry is that VCs should periodically assess their level of IT knowledge using reliable instruments, and strive to develop their knowledge base. Besides, VCs who determine that they are highly knowledgeable have to be cautioned against quick, untested, intuitive judgments because taking time to question the limits of what they know may help them develop a more accurate understanding of what they know and counter overconfidence for these VCs. Indeed, experts in many domains, from chess to investment, take time to develop more accurate self-insight through coaching, for example.

Interestingly, we did not find any indication of influence of IT experience on overconfidence even after controlling for a potential nonlinear effect of IT experience. Ours is not the only study to report this. Extant studies have reported a similar observation: VCs' overconfidence may not depend on their experience (Acs and Audretsch 2006; Zacharakis and Shepherd 2001). The explanation for this nonsignificant effect might be that VCs who are technically more knowledgeable can better recognize an increasing gap between new technical developments and their knowledge. Realizing the gap in their knowledge, technically more knowledgeable VCs may spend more time than the rest to stay abreast of new technical advancements. This could be a possible reason why we do not see any statistical effect of IT experience on VCs.

This study has a few limitations as well. One of these has to do with the fact that not all mediators of the effects we postulated could be measured. So, when we hypothesized that it is the self-attribution bias that leads VCs to become more overconfident following successful funding decisions, we tested only the net result of the prediction—the relationship between past successes and overconfidence—but more detailed experimental studies are needed to test the mediating mechanism. Another limitation of this study is that it focuses only on antecedents of VCs' overconfidence. Future studies should explore how VCs' overconfidence affects their financial performance.

To conclude, our work presents a richer and a more nuanced picture of the role of knowledge for decision making, and the effect of IT knowledge on the overconfidence of VCs in their IT investments in particular. By examining nonlinear effects of IT knowledge, we offered a novel explanation for the contradictory findings concerning the role of knowledge in previous research, as well as pointed out potential pitfalls for VCs with both low and high IT knowledge. By examining the interaction effects of IT knowledge, we shed light on new reasons behind the assertion that IT knowledge is an important qualification of VCs investing in the IT domain.

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