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Brian L. Dos Santos
University of Louisville, brian@louisville.edu

Pankaj C. Patel
Ball State University, pcpatel@bsu.edu

Rodney R. D'Souza
Northern Kentucky University, dsouzar@nku.edu

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Research Article

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Brian L. Dos Santos
University of Louisville
brian@louisville.edu

Pankaj C. Patel
Ball State University
pcpatel@bsu.edu

Rodney R. D'Souza
Northern Kentucky University
dsouzar@nku.edu

Abstract

The success of new ventures can hinge on obtaining venture capital (VC) funding. Virtually every successful IT venture has depended on VC funding early in its history. However, obtaining venture capital is difficult. Unlike earlier studies on VC funding that consider new ventures to be homogeneous, this study seeks to identify factors that VCs consider when they make funding decisions for IT ventures. Building on prior research in the area of agency and business risk, we develop a theoretical model that draws on work in finance and entrepreneurship. The model suggests that VCs consider two types of risk: business risk and agency risk. The relative importance of these two types of risk may be different across industries. We test this model using data from 139 business plans for IT startups that were considered for funding by VCs. Traditional structural equation modeling (SEM) does not accommodate non-normal data or dichotomous outcome variables. Using the Robust Weighted Least Squares approach, we test our model with non-normal data and dichotomous outcomes. In addition, we use Tetrad analysis to check model fit against alternative models, floor and ceiling analysis to test sample frame validity, relative effect size comparison to test relative elasticity of effects, and a Monte Carlo estimation approach to test overall model power and power of individual paths. We find that business risk is an important factor in start-up funding for IT ventures. We do not find agency risk to be an important consideration in start-up funding for IT ventures.

Keywords: *IT industry investments, new IT ventures, business risk, agency risk, entrepreneurship, venture capital, and structural equation modeling*

* Robert Kauffman was the accepting senior editor. This article was submitted on 22nd December 2009 and went through three revisions.

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Venture Capital Funding for Information Technology Businesses

1. Introduction

New ventures that seek to provide an IT product or service are started every day. Some of these new ventures succeed; most fail.[1] Obtaining venture capital (VC) funding is a necessary condition for the success of most new IT ventures. Table A-1 (Appendix) lists a few well-known IT firms and the VC firms that provided start-up funding for these new ventures. Empirical studies have concluded that VC-backed businesses have a higher survival rate than non-VC-backed businesses (Zacharakis and Meyer, 1998). Had the firms in Table A-1 not received VC funding, the products and services available to users (demand side) may have been quite different from what we have today. Although there is a vast amount of management and entrepreneurship literature related to VC funding, VC funding of IT ventures has not been studied. A better understanding of VC funding for IT ventures could help IT entrepreneurs and lead to better survival rates for IT ventures. In turn, better survival rates could lead to higher quality or lower-priced IT products for users.

Venture capital firms are important intermediaries in financial markets, providing capital to new ventures that might otherwise have difficulty attracting financing. New ventures typically are small, young, and plagued by high levels of uncertainty. Moreover, these firms typically possess few tangible assets and operate in markets that change very rapidly (Gompers and Lerner, 2001). VCs finance these high-risk, potentially high-reward, firms, purchasing equity or equity-linked stakes while the firms are still privately held. The venture capital industry has developed a variety of mechanisms to overcome the challenges faced by investors at this stage in a firm's development. For example, VC firms may help a new venture recruit personnel with appropriate technical or managerial skills.

In a recent National Venture Capital Association (NVCA) report, VCs invested $456 billion in 27,000 companies between 1970-2008 (IHS Global Insight, 2009). In 2008 VC-backed firms accounted for 21 percent of GDP, and 11 percent of jobs. In the software, telecommunications, semiconductors, networking and equipment, and electronics and instrumentation industries, VC-funded businesses represent 67 percent, 55 percent, 51 percent, 47 percent, and 44 percent of the revenues, respectively. Clearly, VC investments are a key factor in growth and innovation in the IT industry.

Obtaining VC funding is difficult. Anecdotal evidence suggests that approximately one in 100 business plans is funded by a VC.[2] Moreover, economic conditions have made the competition for VC funds more fierce (PricewaterhouseCoopers, 2010). VC investments dropped from a high of $101.8 billion in 2000, to $17.7billion in 2009. Providing better guidance to IT entrepreneurs may increase the likelihood of obtaining VC funding. Moreover, as discussed below, there is reason to believe that VC funding decisions for IT ventures might be different from VC funding decisions in other industries.

The management and entrepreneurship literature is rife with anecdotal evidence suggesting that VCs consider a few factors (e.g., the quality of the venture team and the potential of the business model) in making investment decisions, but theoretical frameworks have been lacking. However, recent work by Kaplan and Stromberg (2004) and Kaplan et al. (2009) theorizes that VCs consider business risk and agency risk. Business risk can be described as the risk related to the success of a product or service in the market. Agency risk is risk that results from divergent interests of VCs and the entrepreneurs running the firm (Jensen and Meckling, 1976). Drawing on traditional notions of business and agency risk, Kaplan and Stromberg (2004) extend such risks to the VC investment domain.

Extending Kaplan and Stromberg's work, we suggest that the relative importance of business or agency risk to VCs could be contingent on the industry. Specifically, the business risk for new IT ventures may be quite different from the business risk for new ventures in other industries. Many of the most successful IT ventures are those that provided products that created new markets, for example, PCs, information search, etc. The same cannot be said for many very successful non-IT

[1] For the purpose of this study, a new venture is defined as a firm that is seeking its first round of venture capital funding.
[2] Conversations we had with VCs at Mayfield Fund, Cronus Ventures, and Chrysalis Ventures indicate that they fund roughly one percent of the business plans they receive.

ventures, for example, fast food (McDonald's) and retail (WalMart). The agency risk for new IT ventures may also be quite different from agency risk for new ventures in other industries. Many of the most successful IT ventures were started by individuals who had very little management, startup, or leadership experience (e.g., Microsoft, Yahoo, Google, and Facebook). On the other hand, most successful ventures in other industries were launched by individuals with significant management, startup, or leadership experience (e.g., Walmart, and McDonald's). Consequently, VCs could weigh the importance of business risk and agency risk differently for new IT ventures than they do for businesses in other industries. Specifically, in an attempt to understand how VCs decide which new IT businesses to fund, we focus on which of the two key risks, agency risk or business risk, VCs prefer to mitigate when investing in new IT ventures. Additionally, we extend Kaplan and Stromberg's work by weaving in the research on VC funding in management and entrepreneurship. The literature suggests that the market for the product and the competitive environment affect VC funding decisions. We explain why these two factors are important components of business risk in our model.

In addition to developing a general theoretical model that links business risk and agency risk to VC funding decisions, we report on a study that determines whether business risk and agency risk are equally important in VC funding of new IT ventures. Our study uses data obtained from actual business plans for IT ventures that were considered for funding by VC firms.[3] First, three independent groups of practitioners identified criteria they use to make funding decisions, and provided weights for the criteria. A different group of experts then evaluated the actual business plans using the identified criteria. This group of experts evaluated these plans to identify factors that VCs actually use to make funding decisions for IT ventures. Our approach is unusual in that we placed few constraints on the experts as they identified criteria and weights. Instead, we used recently developed extensions to SEM (e.g., Robust Weighted Least Squares, Monte Carlo estimation, and Tetrad analysis) that are particularly well suited to analyze our data and validate the results.

Our results suggest that, for new IT ventures, VCs emphasize business risk over agency risk. Our results differ from most studies on VC funding (e.g., Muzyka et al., 1996, Shepherd, 1999). Our study indicates that a lower business risk suggests a favorable market for the firm's product and a less competitive environment in which the firm will operate. In an attempt to find additional support for our results, we spoke to VCs at three different firms that invest in IT ventures. We report on these conversations at appropriate points in the last section of the paper.

This paper is organized as follows. In the next section we describe the theoretical model that guided this study and develop the four hypotheses that we set out to test in our study. The third section provides a more in-depth report of the data gathering process and the data. The fourth section details our analysis of the data and presents our results. We end the paper with a discussion of the results, conclusions, and limitations.

2. Theoretical Model and Hypotheses

2.1. Theoretical Model

Venture capitalists play a critical role in the development of new ventures by providing capital to high-potential businesses in exchange for partial ownership of the firm. Research has found that VCs also add significant value in the form of strategic planning and recruiting management and as a sounding board for entrepreneurs (Gorman and Sahlman, 1989; Macmillan et al., 1989). In addition, a VC firm's investment provides a strong signal of a new venture's quality and future prospects to stakeholders in task and institutional environments (Chang, 2004). Thus, VCs are central to establishing legitimacy in the institutional environment and enhancing new venture performance in the task environment.

[3] In this study, the IT industry includes firms that produce the products that enable consumers (i.e., individuals and organizations) to obtain and transport information of value to them and firms that actually provide consumers with valuable information. IT industry firms enable consumers to create, store, exchange, access, and use information in its various forms (business data, voice conversations, still images, motion pictures, multimedia presentations, and other forms, including those not yet conceived). For example, Facebook, MySpace, and eBay are IT industry firms.

Venture capital infusions into a company may occur at several points in the life cycle of a business, up to the point that a new venture goes public (i.e., the IPO stage). VCs typically provide capital necessary to establish and grow a firm's operations, once a firm is able to demonstrate product demand (at the start-up stage). Unlike investing in a publicly traded firm where the returns from an investment may be assessed using CAPM, with startups, the information necessary to estimate risk and return is not available, and reasonable estimates are impossible to obtain.[4] Because risk-return information is so difficult to obtain, traditional, theoretically-driven approaches drawn from strategic management, finance, and industrial economics are not easily used. Because of this lack of information, research has focused on identifying criteria that VCs consider when making investment decisions (Shepherd, 1999; Tyebjee and Bruno, 1984).

In evaluating an entrepreneurial venture, a VC deals with two types of uncertainty. Business risk involves the feasibility and market acceptance of the firm's products and the potential competition that can erode profits (Teece, 1987). Mitigating business risk is important from a survival standpoint. The products offered by new IT ventures can create new markets or compete in existing markets using new organizational forms (Brynjolfsson and Hitt, 2004; Mendelson, 2000; Weill and Vitale, 2001). Assessing the business risk of a venture that will create a new market can be difficult because the market for the product is difficult to estimate. If a venture achieves early success in an existing market or a new market, it is difficult to assess how the competitive environment will change. Moreover, business risk cannot be reduced through diversification because the viability of the venture has not been completely established and, therefore, diversified portfolios cannot be created using traditional co-variance-based analyses (Kaplan et al., 2009).

The other uncertainty results from agency risk, the information asymmetry resultant from the different interests of the investor and the entrepreneur that often characterize young firms, particularly in high-technology industries. For example, when a firm raises equity from outside investors, the manager has an incentive to engage in wasteful expenditures (e.g., lavish offices) because the manager may benefit disproportionately from these perks but does not bear their entire cost. VCs must try to ensure that the entrepreneur will act in the firm's best interests (i.e., reduce agency risk). Investors use contracts to deal with these information asymmetries. However, if all the outcomes of the entrepreneurial firm cannot be foreseen (as is often the case with new IT ventures), and the effort of the entrepreneur cannot be ascertained with high confidence, it is difficult to write a contract governing the financing of the firm (Hart and Moore, 1998). These problems are especially difficult for companies with intangible assets whose performance is difficult to assess, as is often the case with IT firms at the start-up stage (Gompers and Lerner, 2001).

VCs would prefer to mitigate risk they can most effectively manage to increase the chances of venture success. However, since agency risks for new ventures are not easily mitigated through contracts, and business risk cannot be diversified in traditional capital markets, the central issue in research on VC investment decisions becomes: Do VCs prefer to manage business risks or agency risks in funding new IT ventures? Building on past research, we develop a theoretical model of the determinants of VC funding decisions.

2.2. Hypotheses Development

2.2.1. Business Risk

Ventures can be viewed as goal-directed open systems that interact with their environment (Aldrich, 1999). As an open system, a venture must acquire resources, negotiate boundaries, and engage in exchanges with stakeholders. The central reason for a venture's failure is an inability either to effectively meet market demands or to survive competitive conditions in an industry (Brush et al., 2008; Morris et al., 2005). Business risk may be mitigated by adopting new ways of conducting

[4] CAPM or the Capital Asset Pricing Model indicates that in a competitive market, the risk premium of an asset is directly proportional to β (the sensitivity of the asset to market movements). Specifically, R, the risk premium on an asset, is determined by: $R = R_f + \beta (R_m - R_f)$, where R_f is the risk-free rate of capital, R_m is the expected market rate of return, and β is a measure of the relative volatility of an investment. CAPM is widely used to price assets when the necessary information about the asset is available. Typically, for startup investments, the necessary information to use CAPM is not available.

economic exchanges. A venture's ability to develop internal tasks and routines to respond effectively to the industry and competitive environment is central to increasing venture survival.

Many new IT ventures have been successful, at least in part, because they developed a novel business model. The essence of novel business models is the conceptualization and adoption of new ways of conducting economic exchanges, which can be achieved by connecting previously unconnected parties, by linking transaction participants in new ways, or by designing new transaction mechanisms. Business model innovation may complement innovation in products and services, methods of production, distribution or marketing, and markets (Schumpeter, 1934). Regardless of the distinctiveness of its product, a firm that practices a different way of operating its business can be successful (Chatterjee, 1998). Novel exchange mechanisms such as connecting previously unconnected parties, linking transaction participants in new ways, or designing new transaction mechanisms can be central to venture success. New organizational structures can also help mitigate business risks. IT advances have made it possible for firms to design new boundary-spanning organizational forms (Dunbar and Starbuck, 2006; Mendelson, 2000). For example, a recent study of Internet firm survival for the 1996-2006 period concluded that a firm's business model affects survival (Kauffman and Wang, 2008). This supports Zott and Amit's (2007) argument that a new venture's business model can be key to its success, creating value either by enhancing a customer's willingness to pay or by decreasing supply and partnership costs through improved transaction efficiency. It is easy to see why VCs pay close attention to a venture's business risk (Arthurs and Busenitz, 2003; Chen et al., 2009; Kaplan and Stromberg, 2004). Therefore, we state the following hypothesis:

> ***H1:*** *VCs prefer low business risk in their start-up investment decisions. (Business Risk Preference Hypothesis)*

The extant management and entrepreneurship literature on VC funding suggests that there are two relatively distinct components of business risk – the market for the product and the competitive environment. The former is customer-related, while the latter is competition-related.

2.2.2. Market for the Product

Typically, new ventures operate in niches, are small, and do not enjoy economies of scale. The market and survival potential of a venture is contingent on the extent to which it can create value through product differentiation. Specifically, the extent to which customers adopt the new product is central. A large potential market with increased likelihood of product differentiation can indicate higher market potential. When ventures create a new market, they may be able to garner first mover advantages by building a loyal customer base and increasing switching costs. The entrepreneurship literature has found support for aforementioned factors enhancing market potential (Robinson, 1999).

Ventures that provide value through differentiation typically perform well (Sandberg, 1986). Ventures typically do not have resources or routines to compete with incumbents in large markets. Product differentiation helps them develop a niche. Focusing on a niche helps ventures develop competencies over time (McDougall et al., 1994). Product differentiation makes it easier for ventures to establish market potential, and the market potential of a product is critical to ensure resource flow and assure customers, suppliers, and financiers of the financial viability of the venture. Therefore, market potential plays a central role in enhancing self-sufficiency of resources and increasing chances of survival.

Compared to large firms, most new ventures lack marketing routines that are efficient (e.g., supply chain) or effective (e.g., brand management). In order to survive, ventures focus instead on increasing market share (Hills et al., 2008). Miles and Darroch (2008) and Morris et al. (2002) explain how the marketing focus of new ventures is significantly different from that of large firms. Hills et al. (2008, pg. 107) state: "Entrepreneurs seemed to think of marketing as a fragmented set of factors that affect sales performance, rather than a substitutable, coherent, comprehensive, and strategic set of demand generating variables that include the traditional marketing mix variables of price, place, promotion, and product." Ventures focus on enhancing market share to develop a stream of revenues necessary for venture growth. Robinson (1999) found that ventures focusing on enhancing market share through a niche focus had enhanced return on equity.

New IT ventures have successfully expanded markets through the use of novel business models (e.g., eBay), successfully competed in existing markets with a differentiated product (e.g., Amazon), and developed new markets (e.g., Zynga). New IT ventures have, over time, expanded into new markets as they develop competencies (e.g., Amazon).

The entrepreneurship literature suggests that VCs also focus on factors affecting market demand. The literature suggests that the customer's view of the product is a key factor in determining the value of a new venture (Kaplan and Norton, 1996) and that product marketability is a key consideration of VCs (Shepherd, 1999; Tyebjee and Bruno, 1984). Prior studies indicate that the likelihood of customer adoption (Kaplan and Stromberg, 2004) and market size (Tyebjee and Bruno, 1984) are also important to VCs. Studies of success and failure of new product introductions in the market suggest that product factors such as uniqueness, differentiation, and entry timing affect new venture success (Cardis et al., 2001; Fichera, 2001). This leads to our second hypothesis:

> ***H2:*** *The business risk of a new IT venture is mitigated by a large market for the firm's products. (Product Market Hypothesis)*

2.2.3. Competitive Environment

The competition that a new venture is likely to encounter affects its success (Chen and MacMillan, 1992). A new venture's competitors can be established firms already competing in that market or firms that enter the market after the venture begins operation. Competitors can also be other new ventures that enter the market at a later date. Consequently, ventures face dynamic competitive conditions, conditions that can be viewed from the SCP (structure-conduct-performance) paradigm in Industrial Organization (IO) economics and the industry life cycle (ILC). The SCP paradigm is a static representation suggesting that the strategic behavior of firms is influenced by the structure of the industry within which the firm operates (Bain, 1968; Mason, 1967). The ILC is dynamic in that it suggests that the strategic behavior of firms is influenced by their life cycle stage (Utterback and James, 1975). Drawing on the theoretical underpinnings of these two approaches, competitive conditions could be more effectively predicted in the context of ventures. VCs prefer to invest in earlier stages of the ILC because in the early stages there may be little competition for the product or service. As competitive conditions stabilize, VCs may begin to rely on the SCP paradigm, which may provide a more effective assessment of competitive rivalry.

The life cycle of the industry is a key factor in predicting competitive success of a venture. Ventures entering the industry during early stages are more likely to benefit from setting product standards, gaining reputation, increasing switching costs, and controlling distribution channels (Lieberman and Montgomery, 1988). Studies in entrepreneurship by Biggadike (1979) and Tsai et al. (1991), indicate that the life cycle stage has an important effect on venture success. Therefore, entry timing is very important.

While the ILC stage at which a new venture enters an industry is important, industry concentration can also have an impact on venture profitability. A higher concentration could affect the extent of competitive retaliation and availability of resources. In high concentration industries, incumbents control key resources and distribution channels. In addition, large firms typically enjoy economies of scope and scale. Therefore, ventures are less likely to succeed in industries with high concentration. Although, ventures could develop a niche, such niches are typically less profitable, and hence, less appealing to VCs. If significant profits could be made from niche offerings, large firms would have greater incentive and capabilities to enter such niches.

The SCP model in IO economics suggests that structural variables are key determinants of firm performance (Bain, 1968). According to Bain (1968, pg. 28), key structural elements are: (1) the degree of seller concentration; (2) the extent of product differentiation; and (3) the condition of entry (entry barriers) to an industry. In the context of young and small ventures, these factors predict demand trends over time. For new ventures, Kunkel (1991) identifies the life cycle stage, industry concentration, entry barriers, and product differentiation as key factors affecting venture success. Miller and Camp (1985) and Stuart and Abetti (1987) find that ventures entering low-entry barrier industries performed better. Also, ventures that are able to increase barriers to entry after entry achieve higher returns (Sandberg, 1986).

There are numerous examples of IT industry firms that have successfully introduced products that created new markets (e.g., PCs), or developed new business models (e.g., online sales of PCs). The pioneers have faced competition from existing firms and from new ventures that enter at a later date. First movers may be irreparably harmed if later entrants can leapfrog the pioneer with a better product, superior technology, or better positioning of the product (Lieberman and Montgomery, 1988). When evaluating a new venture proposal, VCs consider factors that will enable the firm to compete in the market against existing firms or new ventures. A new IT venture that employs a different business model may make it difficult for existing firms to compete (e.g., Dell with online PC sales) or make it difficult for new firms to enter because of large network effects.

Researchers have studied how venture survival is affected by the reactions of established firms to a new entry in the market (Chen and MacMillan, 1992; Ferrier et al., 1999). Others identify conditions that deter market entry (Bunch and Smiley, 1992; Han et al., 2001). Some of the factors that affect the competitive environment that a new venture will encounter include: intellectual property rights held by the new venture (Schneider, 2002); how long it will take competitors to enter the market (Golder and Tellis, 1993); the strategic alliances that a new venture has acquired (Kale et al., 2002; Kaplan and Stromberg, 2004); entry timing (Kaplan and Stromberg, 2004; Shepherd, 1999); and whether the competition in the market is intense, fragmented, or emerging (Kaplan and Stromberg, 2004; Macmillan et al., 1987). This leads to our third hypothesis:

> ***H3:*** *The business risk of a new IT venture is mitigated by a less competitive environment for the firm's products. (Competitive Environment Hypothesis)*

2.2.4. Agency Risk

The principal-agent paradigm has been the primary lens through which the existence of early stage financing for firms has been explained (e.g., Amit et al., 1998). Agency risk stems from the uncertainty that the agent (entrepreneurs) will act in the best interest of the principal (VC). Agency risk increases as information asymmetry between a VC and a venture team increases. Amit et Al. (1998, p.441) state: "We view their (VCs) 'raison d'eˆtre' as their ability to reduce the cost of informational asymmetries." As a result of information asymmetries, VCs have to deal with adverse selection and moral hazard problems.[5] The adverse selection problem refers to the fact that less desirable ventures will choose to involve VCs, whereas more desirable ventures will choose to develop without VC participation. The usual approach to dealing with the adverse selection problem is to have a contract that emphasizes pay-for-performance. A well-designed pay-for-performance contract will increase the likelihood that more desirable ventures will opt for VC financing. This is, however, difficult to do for start-up stage investments because there is little historical data for use in contract design. The moral hazard problem arises because the entrepreneur may not enter into a contract in good faith, or may take risks that the VC would not take (Wiseman et al., 2000). Even if more desirable ventures are attracted by higher pay-for-performance contracts, the issue of post contractual moral hazard still remains. Entrepreneurs may not work as hard, or may create "hold-up" problems once the venture is successful (Kaplan and Stromberg, 2004). A contractual solution to the moral hazard problem is difficult to design at the start-up stage (e.g., a vested shares approach is difficult to design at the start-up stage).[6]

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[5] Adverse selection refers to the fact that agents may misrepresent their abilities (Walsh and Seward, 1990), and may misrepresent the value and risk profile of the business idea (Amit et al., 1998) to a principle. Moral hazard occurs when an agent does not enter into a contract in good faith (e.g., makes a less than optimal effort due to his or her risk and/or effort aversion), or has an incentive to take unusual risks (that the principle would not take) (Eisenhardt, 1989; Wiseman et al., 2000).

[6] Shares are vested if the employee leaves the firm, yet maintains ownership of the shares. In this context, an owner (VC firm) may assign an entrepreneur shares with a vesting schedule that indicates that a percentage of the assigned shares are vested each year.

How do VCs ex ante mitigate these agency problems for firms in the start-up stage? Management teams can increase the chances of success of a new venture; consequently, VCs must determine whether a new venture's management team will mitigate the agency risks inherent in new ventures. Since linking effort to performance is difficult to specify ex ante, Kaplan and Stromberg (2004) suggest that venture team characteristics are the signals that VCs consider to reduce agency risk. They suggest that the quality of a new venture team can be determined by the education, industry experience, and management skills team members possess. While management quality does not guarantee the mitigation of ex ante or ex post agency risk, it does reduce risk for two reasons.

First, a venture team with more invested in the venture because of higher opportunity costs reduces adverse selection and moral hazard. Increased investment in human capital can signal a risk profile similar to that of the VC, since both parties have significant resources at stake. An increase in the alignment of risk profiles between a VC and an entrepreneur will help lower monitoring costs. In addition, with similar risk profiles, fewer conflicts will result, and the team will expend greater effort to develop the business. Fewer conflicts not only reduce agency costs, they also enhance knowledge transfer and coordination between the VC and the venture team (Barney et al., 1996).

Second, VCs have been known to add non-pecuniary value to a venture. Typically, VCs provide guidance to venture teams in their dealings with business risks. By tapping into their industry and market contacts, VCs play an important role in enhancing venture outcomes. When choosing among ventures, VCs must account for the anticipated effort expenditure when helping venture teams. Ventures with better management will require less VC effort and vice versa. If VCs expect to expend great effort on a venture, the compensation for the entrepreneurs will decrease (Kanniainen and Keuschnigg, 2004), increasing adverse selection and moral hazard. In other words, a more competent team will be able to meet equilibrating conditions so that they can receive a better effort-payoff ratio than less competent teams.

While ex post agency risk may be managed ex ante, a better management team creates more effective equilibrating conditions by reducing agency risk. This leads us to our fourth hypothesis:

> ***H4:*** *VCs prefer low agency risk in their start-up investment decisions. (Agency Risk Preference Hypothesis)*

Our theoretical model is depicted graphically in Figure 1.

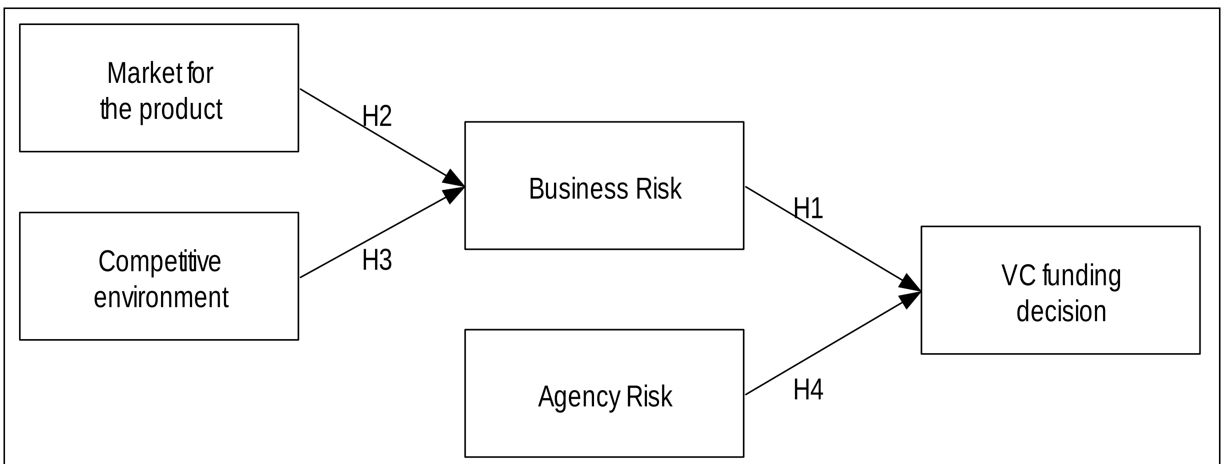

Figure 1. General Model of Venture Characteristics and VC Funding Decisions

3. The Data

Empirical studies on VC funding have been based upon retrospective reporting by VCs (Tyebjee and Bruno, 1984), questionnaire responses (Macmillan et al., 1987), and self-reporting (Hisrich and Jankowitz, 1990). These data sources comprise what Argyris and Schon (1974) refer to as "espoused theories of action," theories based upon what decision makers say they do when making a decision. In contrast, "theories in use" (Argyris and Schon, 1974) are theories derived from decision makers' actions. The data for our study is an example of this latter approach, derived from business plans for IT ventures that were considered for funding by VC firms. Business plans are a good source for information about new ventures. A recent study of 50 new ventures still in business three years following an IPO found that 49 of the firms still maintained their core businesses or business ideas (as described in their business plans at startup) (Kaplan et al., 2009). Only one firm had changed its core line of business to produce a different product or service or had abandoned its initial market segment to serve a different one. Of all non-financial firms that went public in 2004, only 7.5 percent changed their lines of business (Kaplan et al., 2009). This suggests that the information in business plans at start-up can be very useful to VCs in their funding decisions.

We obtained complete business plans for 200 technology businesses that were considered for funding by VC firms on the east and west coasts of the U.S. in 2004. Seventy-two of these business proposals received funding, and 128 proposals did not receive funding.[7] Since VCs typically fund a very small percentage of the business plans they receive, our sample is not representative of all received business plans. However, we believe our sample to be representative of those plans that VCs actively consider for funding since, according to a well-known VC, most plans VCs receive go straight into the trash bin.[8] Ceiling/floor analysis (described later) suggests that most of the businesses that did not receive funding were worthy of serious VC consideration.

In order to determine how VCs evaluate these business plans, we used a two-stage process. In Stage 1 (itself, a three-step process), we determined the criteria and weights that VCs use when evaluating new ventures and making funding decisions. In Stage 2, experts evaluated each plan using the criteria developed in Stage 1. The expert assessments of these business plans reflect how VCs actually make funding decisions. A pictorial overview of the data gathering process is depicted in Figure 2. We describe each stage below.

3.1. Stage 1: Identifying Criteria Used by VCs

In the first step, we identified 22 criteria that VCs use when making funding decisions from the literature. We distributed these criteria and their definitions to a group of approximately 120 VCs, angel investors, and commercial lenders present at a venture club meeting held in a Midwestern U.S. city. Angel investors provide funds (seed capital) to new ventures that they believe will be successful in obtaining VC funding. Some commercial bankers also provide early stage financing, and their presence at the venture club meeting suggests an interest in new venture financing (Gonzalez and James, 2007). We asked these individuals to identify the criteria in the list that they use to determine whether they would invest in a new venture. They were asked to add criteria to the list, if necessary, and to define any criteria that they added. We received fifty-eight usable responses. Respondents added six new criteria, for a total of 28 criteria. We then eliminated seven of the 28 criteria because they appeared on few lists.

In the second step, we presented the remaining 21 criteria to a focus group of 12 additional VCs and angel investors (both institutional and private) from a Midwestern U.S. city who had been lead investors in more than 50 different businesses. This group was asked to: 1) determine whether the

[7] It should also be noted that for most of the funded plans, we only know whether a plan was funded; we do not know how much funding was provided, nor do we have information on terms of the agreement (e.g., percentage of the venture equity obtained by the VC firm, input on governance, etc).

[8] Dr. Yogen Dalal, a managing director with the Mayfield fund and a board member of the Entrepreneurs Foundation, has been in the VC funding business since 1991. Some of his notable investments include Arbor Software, BeVocal, BroadVision, Concur, Nuance, OuterBay, Packet Engines, Snapfish, TIBCO, Vantive, and Whistle. He sits on the boards of numerous start-ups. Prior to joining Mayfield, Dr. Dalal co-founded two successful start-ups, Claris Corporation and Metaphor Computer Systems.

terms and definitions of the criteria were consistent, 2) weight the different criteria in terms of their importance in funding decisions, 3) identify scales that should be used to evaluate each criterion, and 4) group the 21 criteria into meaningful categories.

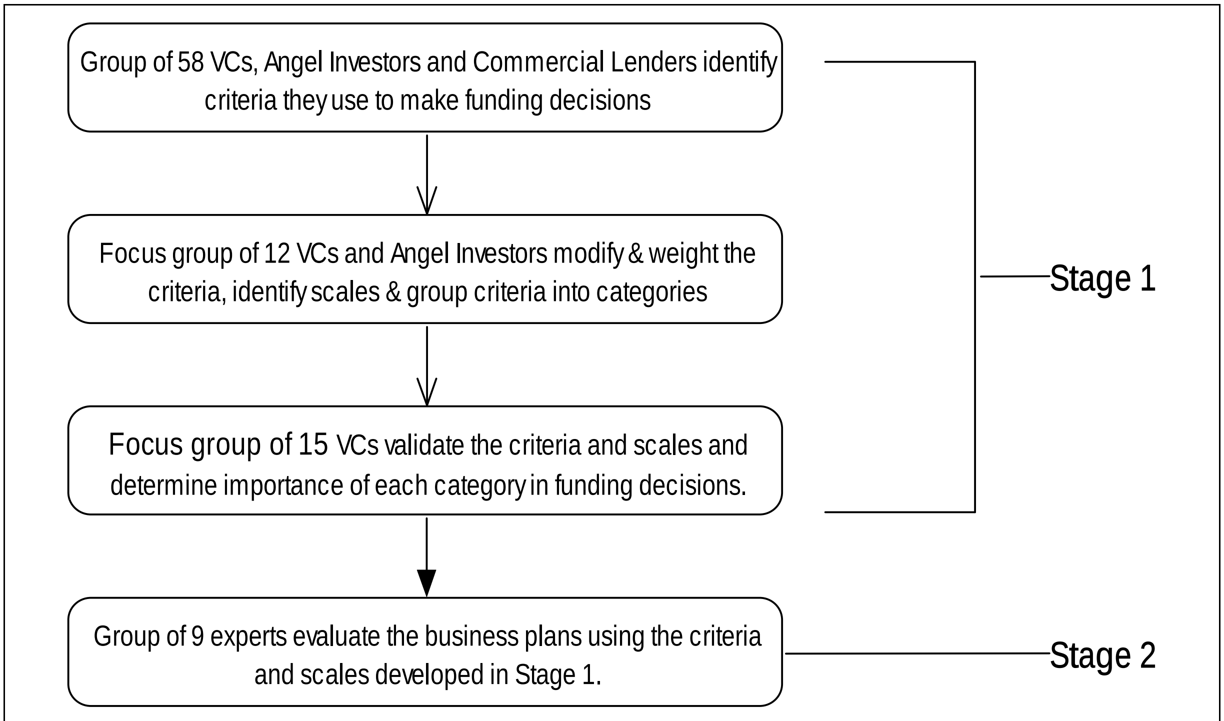

Figure 2. Data Gathering Process

In the third step, we presented the scales, weights, and definitions for each criterion to a second focus group of 15 VCs from a different Midwestern U.S. city. This group was asked to validate or change the criteria and scales, and to determine how important each category was in their funding decisions. We used the data gathered in this stage, together with the data gathered from the previous group, to weigh the different criteria that are important in the VC decision-making process. The criteria and the scales developed at the culmination of this process are shown in Table A-2 (Appendix). In Table A-3 (Appendix), we provide the correlation matrix for the variables used in the analysis.

3.2. Stage 2: Expert Evaluations of Business Plans

In order to evaluate each of the business plans using the criteria and scales developed in Stage 1, we had nine additional experts from a Midwestern city evaluate the business plans. On average, these experts had 18 years of experience with VC funding. We asked them to evaluate the business plans using the criteria and scales developed in Stage 1. It is important to note that none of the experts involved in the two stages were involved in the actual funding decisions for these new ventures.

We randomly distributed a sample of business plans for evaluation by these experts, including an equal number of funded and unfunded plans. Three experts evaluated each plan to reduce the effects of individual bias. The sample included all 72 business plans for firms that received funding and an equal number of randomly selected plans for firms that were not funded, for a total of 144 plans. We chose a balanced sample to improve our ability to assess expert accuracy in evaluating plans, since it is well known that the vast majority of business plans submitted to VCs are not funded. Consequently, even someone with no VC funding expertise will be right more often than not by indicating that a plan fared poorly on all criteria and was not funded. A balanced sample allowed us to determine how well these experts rated the plans based on the criteria. Each expert evaluated an average of two plans per week over a 23-week period in 2005 using the criteria established in Stage 1.[9] In addition to rating each plan on the established criteria, each expert was asked to indicate whether or not a plan should be funded. We discarded one of the VC-funded plans because it received only one evaluation, leaving us with 143 plans, each of which was evaluated by three experts. We discarded four of the evaluated plans because they were for biotechnology businesses (two were funded and two were not funded). We were left with 139 plans for IT ventures that were evaluated by the experts. Sixty-nine of the evaluated plans received funding.

We performed tests on the data to establish the quality and reliability of the ratings. We tested for the degree of similarity in ratings (i.e., inter-rater reliability) and the ability of experts to differentiate funded from unfunded business plans (i.e., the overall funding decision). The inter-expert reliability was 0.93. To assess the extent to which expert funding decisions matched VC funding decisions, we used t-tests and logistic regression. The t-test of the difference between funded and unfunded business plans based on expert ratings was significant ($p<0.01$). In addition, logistic regression, using expert ratings, explained 89 percent of the variance between funded and unfunded plans. These results confirm that the experts provided accurate assessments of these business plans. We computed an average of the three expert ratings on each criterion for each plan, and we used the average evaluations for each plan on each of the criteria in our statistical analysis.

We also sought to determine whether sample business plans were biased (i.e., the unfunded plans were not plans for businesses that had no possibility of being funded). We performed tests to determine whether the ratings for funded and unfunded business plans are unevenly distributed to create artificial separation. Such artificial separation could result in overestimation of effects. If the sample is biased in favor of funded or unfunded business plans, then the item responses for the criteria developed in Step 1 will cluster toward one end of the scale or the other. “Floor” represents the clustering of expert evaluations toward the lower range of a scale for business plans with a low likelihood of funding. “Ceiling” represents the clustering of expert evaluations toward the upper range of a scale for business plans with a high likelihood of funding. If business plans with a lower likelihood of funding cluster toward the floor and those with a higher likelihood of funding cluster toward the ceiling, then the estimates will have artificially reduced standard errors. The literature suggests that floor/ceiling effects should be less than 15 percent of the sample (Nunnally, 1978). The maximum floor effect among all the indicators was 11.51 percent (IP Protection: 16/139), and the maximum ceiling effect among all the indicators was 12.94 percent (Market Size: 18/139). In addition, the skewness statistics should be between -1 and +1 (Nunnally, 1978). We found that the skewness values were well within recommended bounds, ranging between 0.852 and -0.905. Overall, the data does not seem to be overly biased toward funded or non-funded business plans.

4. Analysis and Results

We used a structural equation modeling (SEM) approach to analyze our data, using the constructs in our research model as latent variables. Since our outcome variable was dichotomous (fund/do not fund) and our sample size was not large, we needed to address two potential problems in using an SEM approach. To address these problems, we validated the measurement model and fit the structural model using methods recently developed to handle binary and categorical variables that work well with small samples (Kupek, 2006; Muthén, 1993). We addressed the sample size problem by estimating the statistical power for overall model fit and for key parameter estimates in the model. That is, we determined whether our sample is large enough to have reasonable confidence that we would reject the null hypothesis when it was false. To address one of the major criticisms of SEM-type analysis, we also performed tests to determine whether “alternative plausible models” are a better fit for the data.

The first 15 criteria identified by the experts in Stage 1 were closely related to the constructs in our research model and hypotheses. We eliminated the remaining criteria from our analysis as having little relevance to the structural aspects of new IT ventures and to businesses at start-up. At start-up,

[9] We made certain that the experts did not have any more information about these businesses than was available in the business plans; they were not familiar with the businesses they evaluated.

any financial projections for the business are the entrepreneur's optimistic projections. A recent study of 50 successful new businesses (those still in business three years after an IPO) found that the median company had no revenue in the most recently-ended fiscal year at the time of the start-up stage business plan (Kaplan et al., 2009). Thus, financial data in these plans do not provide information from actual operations. We used the research literature and the criteria identified by experts to map each of the 15 criteria to the constructs in our conceptual model. Literature to support this decision is cited in Table 1.[10] We began by validating the measurement model with tests for convergent and divergent validity. After confirming that the measurement model is valid, we estimated and tested the structural model. We then assessed the robustness of our estimates for overall model fit and for each of the key parameters in our model. Finally, we determined whether an alternative plausible model is a better fit for the data. In Table 2, we provide a summary of our analysis.

Table 1. Mapping Indicator Variables to Constructs

Construct	Indicator	Literature Support for the Indicator
Agency Risk	Startup experience (SE)	[Cooper et al., 1986; Robinson, 1987; Roure and Maidique, 1986; Wells, 1974]
	Industry experience (IE)	[Cooper et al., 1986; Robinson, 1987; Roure and Maidique, 1986; Wells, 1974]
	Leadership experience (LE)	[Muzyka et al., 1996; Wells, 1974]
	Management experience (TE)	[Fried and Hisrich, 1994; Shepherd, 1999; Slater, 1993]
Market for the Product	Market size (MS)	[Andrews, 1987; Kaplan and Stromberg, 2004; Shepherd, 1999; Tyebjee and Bruno, 1984]
	Customer adoption (CA)	[Kaplan and Norton, 1992; Kaplan and Norton, 1996]
	Revenue potential (RP)	[Chaney et al., 1991; Cooper, 2000; Pauwels et al., 2004]
	Entry timing (ET)	[Lilien and Yoon, 1990; Mitchell, 1991; Moore et al., 1991; Pan et al., 1999]
Competitive Environment	Entry timing (ET)	[DeCastro and Chrisman, 1995; Golder and Tellis, 1993; Kaplan and Stromberg, 2004; Macmillan et al., 1985; Shepherd, 1999]
	Competitive market (CM)	[DeCastro and Chrisman, 1995; Macmillan et al., 1985; Macmillan et al., 1987]
	Technological advantage (TA)	[Kaplan and Stromberg, 2001; Mata et al., 1995; McGrath, 1997; Teece et al., 1997]
	Competitive strategy (CS)	[Chen et al., 1992; Ferrier et al., 1999; Macmillan et al., 1985; Robinson, 1987]
	Strategic partners (SP)	[Kale et al., 2002; Kaplan and Stromberg, 2004; Shepherd, 1999; Subramani and Venkatraman, 2003; Wells, 1974]
	Intellectual property (IP)	[Macmillan et al., 1985; Macmillan et al., 1987; Wells, 1974]
Business Risk	Value added (VA)	[Macmillan et al., 1985; Macmillan et al., 1987; Tyebjee and Bruno, 1984; Wells, 1974]
	Product margins (PM)	[Anderson, 1982; Capon et al., 1990; Zirger and Maidique, 1990]
	Market for the Product	
	Competitive Environment	

[10] The VC funding literature suggests that the market for the product is affected by factors such as market size [Tyebjee and Bruno, 1984], customer adoption [Kaplan and Stromberg, 2004], and entry timing [Cardis et al., 2001; Fichera, 2001]. Ventures typically undertake product launches in risky markets, and hence, developing and launching products is central to mitigating business risk. In addition, the competitive environment is central to venture survival. The competitive environment is affected by such factors as: competitive rivalry [Chen and MacMillan, 1992; Ferrier et al., 1999], barriers to entry [Bunch and Smiley, 1992; Han et al., 2001], ownership of intellectual property rights, first-mover advantage [Golder and Tellis, 1993], and strategic alliances [Kale et al., 2002; Kaplan and Stromberg, 2004].

Table 2. Summary of Statistical Analysis

Analysis	Statistical Technique	Reference
Assessment of the measurement model	Convergent Validity	
	Modification Indices	Hair, Anderson et al. [2006]
	Composite Reliability and Variance explained.	
	Discriminant Validity	
	$\chi 2$ difference test for each pair of constructs.	Venkatraman [1989]
	Average variance extracted and correlations among latent constructs.	Fornell and Larcker [1981]
Structural model estimation	Robust Weighted Least squares in Mplus 4.21 with dichotomous outcome variable.	Muthén and Muthén [2004]
Robustness tests	Power Analysis	
	Satorra-Bentler scaled $\chi 2$ for the overall model.	Yuan and Hayashi [2003]
	Power estimates for key model parameters.	Muthén and Muthén [2004]
Alternative plausible model tests	Test of Vanishing Tetrads for categorical indicators	Hipp et al. [2005]
	Nesting of competitive environment and Market for products under Business Risk.	
	Vanishing Tetrads for the overall model.	

4.1. Validating the Measurement Model

We began assessment of the measurement model using confirmatory factor analysis (CFA) for constructs in our research model. CFA is used to establish the validity of relationships between a construct and the indicator variables. We used the robust weighted least squares (RWLS) method for this analysis because RWLS does not require strict assumptions of multivariate normality of the data (Satorra and Bentler, 1994).[11] RWLS also performs well with moderate sample sizes and categorical and ordinal indicators (Muthén, 1993). We used the RWLS procedure in Mplus 2.41, which relaxes the distributional assumptions of the latent variables (i.e., the method does not require normality assumptions). RWLS provides limited information likelihood estimates, robust standard errors, and t-ratios (Muthén and Muthén, 2004).

Based on the research model and criteria mapping, we began by loading 13 of the 15 indicators on three factors: competitive environment, market for products, and business risk. First, we assessed overall model fit. The results for model fit are presented in Table 3.[12] All the model fit indices were within accepted norms.

4.2. Convergent Validity and Internal Consistency

Convergent validity assesses the relevance of indicator variables to the latent variables. We tested for convergent validity to ensure that the indicators measure the relevant underlying constructs (Bagozzi and Fornell, 1982).[13] The literature suggests that the indicator variable "timing" affects the market for the product and the competitive environment. To determine whether timing affects both latent

[11] The scales for our indicator variables were developed by experts, the data does not conform to the typically assumed distribution criteria. Our analysis accommodates our data.

[12] The $\chi 2$ statistic, adjusted goodness-of-fit index (AGFI), RMSEA, and the standardized root mean square residual (SRMR) assess the degree to which the model replicates the actual covariance matrix derived from the data. The $\chi 2$ value is small and insignificant ($\chi 2/df=2.751$), indicating that the null hypothesis of covariance matrix equality cannot be rejected. The SRMR measures the residual variance of all the variables. Smaller values indicate less unexplained variance; lower values indicate better model fit [Gefen et al., 2000]. Adjusted goodness-of-fit (AGFI) values range from 0 to 1. AGFI compares the proposed model with the null model (single-factor model with no measurement error). A value of 1 indicates a perfect fit. RMSEA measures the degree of error per unit degree of freedom. Suggested values for a good fit should be between 0.05 and 0.08 ([Hair et al., 2006] (pgs. 653-661).

[13] We used the iterative procedure based on modification indices [Jöreskog, 1993] to test for convergent validity. For each latent variable, only one item was dropped in each step; standardized factors loadings were set to be a minimum of 0.7 (indicator reliability of at least 0.49) [Jöreskog, 1993]. The analysis was conducted with MPlus 4.21. Convergent validity can be improved if the modification index is greater than 10 [Muthén and Muthén, 2004]; there was no significant improvement for any of the constructs.

variables, we tested models with timing affecting each of these latent variables independently (i.e., one and not the other) against the model where timing affects both latent variables. We found that the model with timing loading on both latent variables improved reliability. When timing is added as an indicator variable for market for products, the modification index (MI) improves significantly, with an increase of 16.53. For a competitive environment, there is no significant improvement by dropping any indicators. Thus, we conclude that timing affects the market for the product and the competitive environment. The results for the modification index analysis for all constructs are shown in Table A-4 in the Appendix. Section B in Table A-4 shows the results for our analysis of the loadings for the "timing" indicator variable.

Table 3. Goodness of fit for CFA Measurement Model

	Initial Model	Desired Level
Total items	13	
χ^2	167.852	Smaller
df	61	
χ^2/df	2.751	<3.0
AGFI	0.908	>0.8
Standardized RMR	0.039	<0.05
RMSEA	0.060	0.05-0.08
CFI	0.956	>0.9

We assessed internal consistency of constructs by determining the composite reliability and variance extracted of each construct. Composite reliability assesses the extent to which a latent variable is measured well by its indicators, while variance extracted measures the degree to which indicators are representative of the constructs. The results for composite reliability and variance extracted are shown in Table 4. All composite reliability values exceed the suggested norm of 0.7 (Nunnally, 1978), and variance extracted values exceed the suggested norm of 0.5 (Hair et al., 2006).

The cross-loading of "entry timing" requires further discussion. Kenny et al. (1998) suggest that double loading is acceptable when it is theoretically relevant. Drawing on the literature review presented in Tables 1 and A-2, entry timing affects competitive and market-based outcomes. From the competition side, early entry by IT industry firms can be important because of switching costs and entry barriers. From a market potential standpoint, early entry can be important for products with large network externalities.

Table 4. Estimates of Composite Reliability and Variance Extracted

Dimensions	# Items	Reliability	Variance Extracted
Competitive Environment	6	0.84	0.66
Market for Products	4	0.85	0.73
Agency risk	4	0.81	0.64

Although double loading can be theoretically justified, empirically, double loading can lead to identification problems because of high correlation among items across two latent factors. Double loading increases covariance between two latent constructs and may lead to (1) an inability to identify unique latent variables and (2) an artificially inflated model fit due to increased covariance. To assess whether double loading is empirically valid, Kenny and Kashi (1992) suggest that the measurement model must meet three conditions: (1) at least three indicators in each construct must have errors that are uncorrelated to each other; (2) of the remaining indicators on either construct, there should be no theoretical justification for correlated errors in measurement; and (3) there must a nonzero loading on at least one indicator for each construct. In our analysis, all three conditions are met. Finally, to control for any other residual correlation, we modeled correlation between latent constructs "market for product" and "competitive environment" (Φ=0.216; Figure 1). Overall, double loading of "entry timing" was theoretically valid and empirically reliable.

Some of our factor loadings were just below acceptable thresholds, but a modification indices approach did not show improvement in model fit. According to Nunnally (1978), lower loadings are to be expected when new measures are being developed.

4.3. Discriminant Validity

Discriminant validity assesses the extent to which constructs differ from each other. We performed two tests to assess discriminant validity. One of the tests for discriminant validity is the χ^2 difference test. For each pair of constructs, we compared the fit of the full model with the fit of a model where the two constructs were not distinct; that is, by setting the correlation between the two constructs to 1. Constraining the correlation between a pair of constructs to 1 forces all items to measure the same construct. A significant difference in χ^2 values between the two models would indicate support for discriminant validity (the constructs are distinct). Table 5 reports all three tests pertinent to our research model. All the χ^2 difference values are significant at the 0.01 level, indicating that the constructs differ.

Table 5. Assessment of Discriminant Validity

Dimensions Model	Constrained χ^2 (df)	Unconstrained χ^2 (df)	$\Delta(\chi^2)$
Competitive Environment with			
Market for products	40.58 (26)	35.45 (25)	5.13 **
Agency Risk	55.14 (35)	42.83 (34)	12.31 **
Market for products with			
Agency Risk	24.97 (20)	18.36 (19)	6.61 **

* p<0.05, ** p<0.01

We also use the "average variance extracted" approach to assess discriminant validity of the constructs (Fornell and Larcker, 1981) (Table 6). The diagonal elements show the variance extracted by each construct, while the non-diagonal elements demonstrate the correlations between constructs. The low correlations among the latent variables indicate a high level of discriminant validity (Bagozzi and Fornell, 1982). After establishing convergent validity, internal consistency, and discriminant validity of our constructs, we proceeded to assess the structural model.

Table 6. Average Variance Extracted and Correlations†

	Competitive Environment	Market for Products	Agency Risk
Competitive Environment	0.66		
Market for Products	0.216	0.73	
Agency Risk	0.229	0.112	0.64

† The diagonal elements are the variance extracted, while the non-diagonal elements are correlations. The "average variance extracted" measures the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error and is determined as follows:
$\left(\sum \text{squared factor loadings}\right) / \left(\sum \left(\text{squared factor loadings} + \text{error variances}\right)\right)$ [Fornell and Larcker, 1981]. If the average variance extracted is less than 0.50, then the variance due to measurement error is greater than the variance due to the construct (i.e., values above 0.50 are good).

4.4. Model Testing

The RWLS procedure used for this analysis is particularly relevant because it is less prone to errors with smaller samples (Flora and Curran, 2004). When the observed variables in a CFA are categorical, the use of maximum likelihood estimation (normal distribution assumption) can lead to inaccuracies (Flora and Curran, 2004). Weighted least squares (WLS) estimation has been shown to be effective with dichotomous or ordinal variables but requires large sample sizes for accurate estimation (Flora and Curran, 2004). In contrast to WLS, RWLS does not appear to suffer from these problems when the sample size is relatively small and may be preferred in most situations with categorical indicators (Flora and Curran, 2004). In fact, the estimates and test statistics obtained with RWLS are reasonably stable for dichotomous data with samples as small as 100 (Flora and Curran, 2004).

The results from RWLS estimation with standardized parameter values are shown in Figure 3. In Table 7 we report goodness of fit indices for the model. The model in Figure 3 explains 61.4 percent of the variance in VC funding for new IT ventures. These results provide support for the Business Risk Preference Hypothesis (H1), Product Market Hypothesis (H2), and Competitive Environment Hypothesis (H3). The Agency Risk Preference Hypothesis (H4) is not supported by the data. We discuss this unusual result at length later.

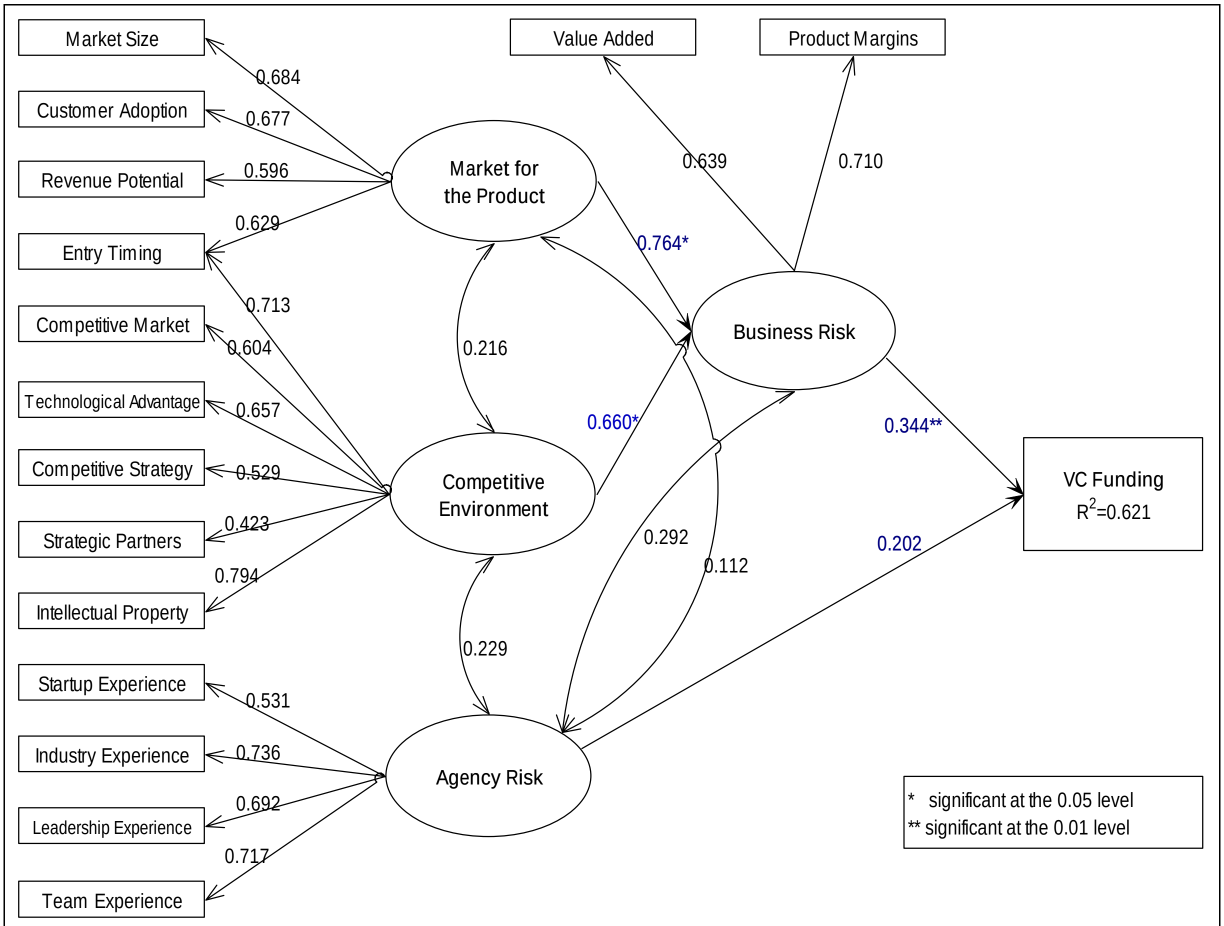

Figure 3. Results of Analysis for the VC Funding Model

Table 7. Goodness-of-Fit Indices for the Final Model		
	Model	**Desired Levels**
χ^2	143.708	Smaller
df	97	
χ^2/df	1.481	<3.0
CFI	0.913	>0.9
TLI	0.904	>0.9
RMSEA	0.064	0.05-0.08

4.5. Robustness Tests

Robustness tests are used to assess the degree to which a model is valid under alternative contexts. In our study, there were two issues that needed attention: the size of the sample and the possibility that alternative models may explain the same phenomenon.

Our sample size is smaller than many of the samples used in earlier studies in the IS literature where SEM has been used. The biggest problem with small sample sizes is a statistical power problem, that is, the power to reject false models (i.e., hypotheses). To address this problem, we used two independent methods to determine whether our sample is adequate to assess model fit. We assessed the power of the overall model using the Satorra–Bentler scaled $\chi 2$ (Yuan and Hayashi, 2003). We also assessed power for each of the estimates that relate to our hypotheses. Finally, we used a vanishing tetrads approach to determine whether alternative plausible models provide a better explanation for VC funding of IT ventures.[14]

4.6. Model Power Tests

We performed power tests to ensure the likelihood of type 2 errors is not high. We used the Satorra-Bentler rescaled $\chi 2$ test to assess the level of power of the overall model, a bootstrap-based inference method that uses the covariance structure (Yuan and Hayashi, 2003). Historically, the rescaled likelihood ratio statistic has been considered a robust test for non-normal data (Hu et al., 1992). However, it has been theorized that for small and medium-sized samples, the statistical adjustments for re-scaled $\chi 2$ may not provide accurate estimates (Bentler and Yuan, 1999), suggesting that bootstrap methods are better under these conditions (Yuan and Hayashi, 2003). We followed Yuan and Hayashi's (2003) bootstrap-based power approach to more accurately assess the overall model power. Using this method, the Satorra–Bentler scaled $\chi 2$ test indicates a power of 83.70 percent. This power estimate is above the norm (i.e., 0.8). Thus, we have reasonably good confidence that our analysis will reject false models.

While power estimation for overall model fit is important, it is at least as important to assess power for individual parameters, since key results (i.e., our hypotheses) are determined by individual parameter estimates. Accordingly, we assessed power for each of the estimated parameters that relate to our hypotheses using a Monte Carlo method developed by Muthén and Curran (1997) and Muthén and Muthén (2002).[15] Business Risk and Agency Risk had parameter estimates of 0.5; Competitive Environment and Market for Products had estimates of 0.25 each. In the second step, we analyzed the mean covariance matrix obtained in Step 1 with the model that misspecifies a parameter of interest by fixing it to zero, and set the number of observations to 139. In the third step, we used the $\chi 2$ value obtained from Step 2 as a non-centrality parameter. We then assessed the model's power to detect misspecification using a SAS routine where degrees of freedom equaled one, the critical $\chi 2$ value for a p value of 0.05 equaled 3.8414, and the approximate non-centrality parameter equaled

[14] A forthcoming paper suggests sample sizes in many published IS studies are too low (Westland, 2010).

[15] We estimate the power to detect whether each of the key parameters in our model is different from zero. As explained by Muthén and Muthén [2002], the process requires three steps. In the first step, we create a mean vector and covariance matrix for the hypothesized parameter values in the proposed model. We specify our model with all parameters fixed to the population values. Because we do not have extensive prior research to estimate population parameters, we weight the parameter inputs equally.

9.286.[16] We conducted this analysis using the Mplus 4.21 and SAS. The power for each of the key parameter estimates is reported in Table 8. The power for all of the parameters is adequate (≥0.8).

Table 8. Power Estimates for Model Parameters†	
Parameter	**Power**
Competitive Environment to Business Risk	0.83
Market for product to Business Risk	0.81
Business Risk to Investment	0.85
Agency Risk to Investment	0.82
† Estimates are significant at the 0.05 level for all models. The critical χ^2 value for a p-value of 0.05 is 3.841. All the values were significantly larger than 3.841. There were 139 observations.	

4.7. Alternative Models Tests

One of the well-known problems in SEM analysis for research seeking to demonstrate causality is the possibility that alternative models may explain covariances in the data as well as or better than the research model. In order to determine whether our theoretical model is a better fit than other plausible models, we used the vanishing tetrad test (Hipp et al., 2005).[17] The vanishing tetrad test is a confirmatory test wherein we specified the models to be tested in advance. Tetrad tests were originally developed for continuous variables, assuming variables are multivariate normal (Bollen and Ting, 1993). A recently developed method enabled us to use the tetrad approach with categorical data (Hipp et al., 2005). This method uses the polychoric correlation matrix (PCM), the asymptotic covariance matrix (ACM), and the model-implied covariance matrix (Hipp et al., 2005; Lee et al., 1995). Polychoric correlations are correlations between two observed ordinal variables. In addition, with the dichotomous decision outcomes (fund vs. do not fund), we used tetrachoric correlations between dichotomous variables. By using PCM and ACM, this approach accounts for the ordinal structure of the data. We used the vanishing tetrads approach to test the research model and to determine whether it was a better model of VC funding decisions for IT ventures. The results of tests ensured that our model is not ad-hoc; there are no plausible models that fit better.

We used the new SAS macro (CTANEST1) for the vanishing tetrad analysis (Hipp et al., 2005). Hipp, et al. (2005) provide a brief yet excellent overview of this method and the use of this macro. We first tested for vanishing tetrads in our research model to test nesting of the competitive environment and market for the product under business risk. By doing so, we determined whether the constructs of competitive environment and market for the product require separate estimations, or should be operationalized through business risk. We tested the nested model in conjunction with these two models by comparing vanishing tetrads in nested and non-tested models. If the difference between the two models were significant, then the null (H_0: τ_{ghij}=0) is rejected and the nested structure is a good fit. Alternatively, tetrads are non-vanishing when the two constructs are independent. Our analysis indicated that the null hypothesis is rejected (H_0: τ_{ghij} = 0). We conclude that competitive environment and market for products are a part of the larger construct, business risk ($\chi 2$ = 6.289; df = 2; p = 0.033).

[16] Data Power; DF=1; Crit=3.841459; Lambda=9.286; Power=(1-(PROBCHI(Crit,DF,Lambda))); Run;

[17] The vanishing tetrad method is an alternative to traditional SEM analysis [Bollen and Ting, 1993]. While SEM methods work with variances and covariances, Tetrad analysis works with relations between sets of four covariances at once. A tetrad is the difference between the product of a pair of covariances and the product of the other pair of covariances among four random variables [Bollen and Ting, 2000]. A tetrad for four observed variables *g, h, i,* and *j* is defined as $\tau_{ghij} = \sigma_{gh}\sigma_{ij} - \sigma_{gi}\sigma_{hj}$, where σ is the covariance between the subscripted variables. To assess the validity of alternate models, the search algorithm in tetrad creates a subset of measured variables for a factor model; at least four indicators (measured variables) per factor are required. For example, if there are four variables, namely, X_1, X_2, X_3, and X_4, there will be three tetrad difference equations. A structural equations model often implies that certain tetrads should be zero. These vanishing tetrads provide a means to test structural equation models. If a model is correctly specified, then, based on the model, certain tetrads should be zero. Thus, we test the null hypothesis: τ = 0 for vanishing tetrads. If the null hypothesis is accepted, the model is correctly specified. In this study, a significant advantage of the tetrad method is that it provides a natural test of nested models for categorical data using the polychoric correlation matrix.

We also tetrad-tested the overall model to assess if alternative covariance structures exist. In this case, if the model does not have vanishing tetrads, the model does not account for significant covariances and, hence, must be revised. Alternative models may either account for additional covariance, or have similar covariances but different relationships. We tested the overall model for vanishing tetrads and failed to reject the null hypothesis ($\chi 2=87.012$; df=88; p=0.689), which indicated that our model was adequate. These tests are additional tests of the validity of our model, beyond commonly-used fit indices in SEM analysis.

4.8. Tests of Effect Sizes

Although agency risk estimation was not significant in explaining investment decisions compared to business risk, we conducted a few additional tests to determine whether agency risk was significantly different from business risk in funding decisions. First, we compared estimations of business and agency risk using lincom in Stata 11. The null hypothesis ($H_{agency\ risk}=H_{business\ risk}$ p=0.013) was not supported. The effect of business risk was significantly different from the agency risk effect.

We also compared effect sizes of scalar values of agency risk and business risk between funded and non-funded ventures. We used a number of measures to compare effect sizes such as Cohen's d, correlation coefficient (r), η2, and area under curve (AUC).[18] In Table 9, we show differences in effect sizes. We began by splitting the sample into funded and non-funded ventures, and calculated differences in effect sizes on scores of agency risk and business risk. We then determined if the difference in effect sizes was significant. In Table 9, we see that the effect size of business risk is significantly higher for funded business plans, and the difference in effect sizes is significant across all the effect size estimations. Business risk is more important in funding decisions for IT ventures.

Our analysis indicated that the firm's business risk is an important consideration for VCs in the funding of IT ventures and that the agency risk is not an important consideration in these decisions. In addition, our results indicate that the business risk of a new IT venture is determined by the market for the firm's products and the competitive environment the firm will encounter.

Table 9. Comparison of Effect Sizes (1=Funded; 0=Not-funded)

	Cohen's *d*	Correlation coefficient (*r*)	η^2	Area under curve (*AUC*)
Agency Risk	-0.216	0.1074	0.0115	0.4393
Business Risk	0.7021	0.3312	0.1097	0.6902
Z-value of difference (Business Risk minus Agency Risk)	3.025***	3.506***	3.089***	4.057***
*** p<0.001				

5. Discussion

This study sought to identify the factors important in VCs' determinations of whether IT ventures should receive funding. The extant literature suggests that business risk and agency risk are important considerations in VC funding. Strikingly, our study found that agency risk is not a significant factor in VC funding of IT ventures at start-up. This should not be interpreted as suggesting that the qualifications of the venture team are unimportant. Obviously, a specific person or group has to have

[18] While all these effect size estimates are widely used (Cohen, 1988), AUC requires some discussion, because it is a nonparametric approach that does not require distributional assumptions as do other assessments of effect sizes. Cohen's *d* is used when two populations being compared are continuous and normally distributed. This condition is not met by our sample. The size of correlation coefficient (*r*) depends on base rate estimates of agency and business risk in the funded and non-funded business plan populations. η^2 suffers from similar drawbacks as (*r*). Given these limitations, AUC is preferred as a non-parametric approach that is independent of the underlying distribution. AUC is the probability that a score (agency risk or business risk) drawn at random from one sample or population (e.g., funded) is higher than that drawn at random from a second sample or population (e.g., non-funded scores).

the initial idea and try to start the firm. However, in contrast to non-human assets (specific to business risk), our results indicate that it is possible for a new IT venture to receive VC funding even if the venture team does not possess the right characteristics, as identified in the literature to date. This result is consistent with the view that the human capital of VCs is important. VCs play an important role in finding replacements (Hellman and Puri, 2002). Until recently, in virtually every empirical study that identified factors that determine the success of new ventures and in studies identifying the criteria that VCs use to make funding decisions, venture team characteristics (i.e., agency risks) was found to be important (Muzyka et al., 1996; Shepherd, 1999). One possible reason for the difference between our results and previous studies is that our study was restricted to IT ventures. There are many plausible explanations for why the criteria that VCs use to determine whether they fund an IT venture may be different from the criteria used to fund businesses in most other industries. The literature suggests that the survival of new ventures is different in technology-intensive industries. Generally, a smaller-scale entry (typical of new start-ups) into a market is associated with a lower likelihood of survival. However, this relationship does not hold for technologically-intensive products (Agarwal and Audretsch, 2001). Even in mature industries that are technologically intensive, entry may be less about radical innovation and more about filling strategic niches, thus negating the impact of entry size on the likelihood of survival (Agarwal and Audretsch, 2001).

Another plausible explanation for the result may be the history of success in this industry. Many new IT ventures, including some of the most successful firms in recent years, have been started by individuals with little or no business, management, start-up, or leadership experience. Hence, VC firms that fund IT ventures are more likely accustomed to dealing with entrepreneurs who do not possess the kind of experience they seek in other industries. VCs who invest in these ventures have likely developed processes to enable them to protect their investments. For example, VCs can insist that the entrepreneurs allow them to bring in individuals with the necessary skills to help manage the business, as a condition for funding the business.

The methods used in past VC funding studies may also explain the results. In the expert systems development community, it is widely known that experts have a great deal of difficulty articulating how they make decisions (Moody et al., 1998). Most of the empirical VC funding research to date has been based upon self-reporting by venture capitalists (experts); prior studies report “espoused theories” (Argyris and Schon, 1974). Our results are based on “theories in use” (Argyris and Schon, 1974). We analyzed data obtained from actual business plans that were considered for funding. Thus, while VCs might claim that the capabilities of the venture team are important in mitigating agency risk, when making these decisions, they may in actuality fund IT ventures where the entrepreneurs do not have requisite skills.

In an attempt to identify other explanations for these findings, we interviewed Dr. Yogen Dalal, a well-known VC.[19] We learned from him that his firm does not consider the characteristics of the venture team overly important. Rather, his firm’s primary concern is that the entrepreneurs are individuals who are easy to work with because his firm is able to bring in high-quality individuals to manage a business if the entrepreneurs work well with others. If the entrepreneurs are difficult to work with, his firm will not invest in the business. In our study, there were no criteria related to this attribute of the entrepreneurs. The same explanation was recently echoed by two other VCs who specialize in IT ventures.[20, 21] There was no indication anywhere in the literature that such criteria should be included, nor did the experts involved in the development of the criteria in Stage 1 suggest that such criteria were important. One of the VCs we spoke to presented another possible explanation for our unusual finding for IT industry firms.[22] He stated that a high-quality venture team lowers downside risk, but does not increase upside potential. The literature suggests that VCs invest in ventures that have high

[19] Personal communications with Dr. Dalal (September, 2007). Dr. Dalal’s qualifications relevant to venture capital were presented earlier.
[20] Personal communications with Mr. Vijay Vashee (April, 2010). Mr. Vashee, a principal with Cronos Ventures, has been investing in new IT ventures since 2001. Prior to that, he worked at Microsoft for 18 years in technical and senior management positions.
[21] Personal communications with Mr. Matt Winn (April, 2010), a senior associate with Chrysalis Ventures since 2005. Mr. Winn has been involved in funding ventures in the healthcare and technology industries.
[22] Mr. Matt Winn.

variance, but can somehow contain costs (McGrath, 1999). Since many IT firms can scale at little additional cost, VCs can focus on the market potential with IT ventures.

Two very recent studies support this finding. A study of the evolution of 50 successful new ventures (from business plan to IPO) found that new venture teams play a limited role in the eventual success of a venture. While new venture teams may be important, their importance is overshadowed by product characteristics and competitive conditions (Kaplan et al., 2009). Another study involving a meta-analysis of 11,259 new technology ventures established between 1991 and 2000 found that venture team characteristics played a limited role in venture survival (Song et al., 2008). It appears that the limited importance given to venture teams by VCs reflects their importance to venture survival. Although our findings are surprising in the context of earlier venture capital funding studies, more recent evidence concurs with our findings.

5.1. Implications for Research and Practice

This work should be of interest to IS researchers because the key research questions for the IS community are greatly affected by the products produced by IT ventures. For IS researchers, it should encourage research that addresses questions related to the creation, development, and growth of new IT ventures. The importance of information technologies to businesses and society in the future is dependent upon the continued availability of new IT products and services. As firms move further away from in-house development of applications, the importance of the IT industry increases. IT industry products and services will determine the important research issues in our field. Answering questions that could contribute to the development of an innovative and robust IT industry clearly is important. We must strive to help new IT ventures succeed.

As indicated earlier, there is an ongoing debate in the VC literature concerning the relative importance of a young company’s business risk and agency risk to the company’s success. While VCs try to invest in companies with low business risk and low agency risk, different VCs claim to weigh one or the other more heavily at the margin. Our results suggest that for new IT ventures, VCs place less importance on agency risk. It suggests that the requirements for VC funding may differ on another dimension, namely, the type of business or industry. This issue needs to be re-examined by studying VC funding in different industry segments.

This work also raises flags regarding the usefulness of information gathered from experts who are asked to report on their decision processes. Further investigation of VC funding of new IT ventures should seek to understand the processes that VCs use to mitigate agency risk when they fund businesses where the teams have little prior experience.

These results also have important implications for entrepreneurs attempting to start new IT ventures. Entrepreneurs need not build a team with the right characteristics prior to seeking VC funding. VCs will fund a good product idea and business plan, even if the entrepreneurs do not have the skills necessary to execute the plan.

5.2. Limitations and Future Research

This study has limitations. The business plans analyzed in this study were those considered by VCs in 2004. Results could be different for other periods. In addition, the VC funding process can be lengthy (weeks or months) and drawn out, with interaction between the VCs and the business teams. While this process is not considered in this study, it is pertinent to funding decisions. During this process VCs may gather information that could affect their decisions. However, as noted earlier, the fact that the experts evaluating the business plans reached the same funding decisions in a large majority of the cases as the VCs suggests that the “due-diligence” process used by VCs did not make much difference in their decisions in these cases. Even so, determining the nature of these processes and their effects on VC decisions would improve our understanding of VC funding of IT ventures. Finally, we do not consider potentially important factors that could affect funding decisions such as the amount of the investment and terms of the funding agreement (Arthurs and Busenitz, 2003; Chen et al., 2009; Kaplan and Stromberg, 2004).

There have been few studies by IS researchers that have sought to identify factors that lead to successful IT ventures (for example, Kauffman and Wang (2007)). Given the importance of the IT industry to IS researchers and professionals, there ought to be more research seeking to understand how VCs affect the success of new IT ventures.

6. Conclusion

The development and use of IT in organizations over the past three decades have been greatly affected by technologies developed by new IT ventures born during this period. Without the IT products offered by firms such as Microsoft, Oracle, Dell, Google, and hundreds of other IT firms, the use of IT in organizations could never have evolved the way it has. IT industry firms that now provide many valuable products to firms and individuals may never have done so without VC funding. To the best of our knowledge, there has been no research that has sought to understand how VCs determine which IT ventures to fund. The model we developed suggests that VCs consider two types of risk: business risk and agency risk. We tested the model using data from 139 business plans for IT start-ups. Results indicate that business risk is an important factor in start-up funding for IT ventures. However, we did not find agency risk to be an important consideration in start-up funding for IT ventures.

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Appendix

Appendix A.

Table A-1. Recent VC Funding for Some Well-Known IT Ventures

Firm	Some of the VC firms that provided funding
3Com	Sequoia Capital; Mayfield
Double Click	Canaan Partners; Bain Capital Ventures; Greylock Partners
Facebook	Greylock partners; Meritech; Accel partners
Google	Sequoia Capital; Kleiner Perkins Caufield and Byers
Hotmail	Draper Fisher Jurvetson
Iwon.com	Bain Capital Ventures
Lifelock	Kleiner Perkins Caufield and Byers
LinkedIn	Sequoia Capital; Bessemer Venture Partners; Greylock Partners
LSI logic	Sequoia Capital
Match.com	Canaan Partners
Paypal	Blue Run Ventures
Redhat	Greylock partners
Sandisk	Mayfield
Shutterfly	Mohr Davidow Ventures
Skype	Draper Fisher Jurvetson
Snapfish	Mayfield
Verisign	Bessemer Venture Partners
Yahoo	Sequoia Capital
YouTube	Sequoia Capital

Table A-2. The Instrument Used by Experts to Evaluate Business Plans

No.	Criterion	Characteristic (Weights)		
1	Market Size	Large rapidly growing market (40)	Large market amenable to rapid growth (30)	Mature shrinking market (-40)
2	Customer adoption	Customer adoption likely (40)	Customer adoption possible (20)	Unpredictable customers (0)
3	Revenue Potential	Significant revenue generated (40)	Revenue Generated (30)	Potential for revenue (20)
4	Competitive market	Insignificant competition and or emerging industry (30)	Fragmented competition with no dominant players (20)	Intense rivalry among existing companies, substantial barriers to entry. Numerous substitutes exist (-30)
5	Competitive strategy	Effective distinctive and sustainable strategy (50)	Potential for replication (0)	Ineffective or easily replicated (-50)
6	Entry timing	Optimal time to enter the industry (50)	Ambiguous industry trends - timing uncertain (0)	Unadvisable to enter the market under current industry conditions (-50)
7	Intellectual Property	Strong IP position (25)	Moderate IP position (15)	Weak IP position (-25)
8	Technological advantage	Relevant technological advantage, unique product / service characteristics (25)	Dormant technology (15)	Disruptive technology (10)
9	Value Added	High Value (Significant customer need solved effectively) (100)	Moderate Value to customers (50)	Low to minimum impact (-100)
10	Product Margins	High Margin (100)	Moderate Margin (50)	Low Margin (-100)
11	Startup experience	Entrepreneur has substantial startup experience (50)		No relevant startup experience (-50)
12	Industry experience	Entrepreneur has pertinent Industry experience (50)		No relevant industry experience (-50)
13	Leadership experience	Entrepreneur has CEO experience (50)	Entrepreneur has High level management experience (25)	Entrepreneur has Leadership experience (10)
14	Team experience	Well balanced, team and goal oriented (100)		Weak team(-100)
15	Strategic Partners	Existing network of value adding strategic partners (25)	Partnership opportunities exist (10)	Unable to obtain strategic partners (0)

Table A-3: Variable Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Invest (Yes/No)	1															
Market Size	0.15	1														
Customer Adoption	0.10	0.60	1													
Revenue Potential	0.08	0.84	0.72	1												
Entry Timing	0.09	0.78	0.77	0.72	1											
Competitive Market	0.11	0.42	0.31	0.35	0.67	1										
Technological Advantage	0.12	0.41	0.33	0.20	0.59	0.57	1									
Competitive Strategy	0.08	0.38	0.38	0.29	0.62	0.70	0.77	1								
Strategic Partners	0.09	0.39	0.28	0.37	0.77	0.72	0.78	0.64	1							
Intellectual Property	0.15	0.30	0.24	0.30	0.74	0.80	0.75	0.70	0.77	1						
Value Added	0.11	0.37	0.22	0.34	0.30	0.29	0.30	0.32	0.32	0.32	1					
Product Margins	0.17	0.32	0.38	0.31	0.32	0.24	0.34	0.33	0.30	0.28	0.78	1				
Startup Experience	0.05	0.38	0.33	0.37	0.28	0.24	0.32	0.40	0.38	0.17	0.33	0.37	1			
Industry Experience	0.04	0.30	0.29	0.39	0.29	0.48	0.29	0.42	0.34	0.29	0.35	0.33	0.67	1		
Leadership Experience	0.03	0.42	0.30	0.30	0.22	0.39	0.32	0.28	0.28	0.42	0.37	0.38	0.71	0.69	1	
Team Experience	0.02	0.35	0.26	0.27	0.27	0.37	0.33	0.34	0.31	0.25	0.22	0.39	0.68	0.63	0.58	1

Table A-4: Results for Modification Index Analysis†

Indicators‡	# of items	df	χ^2	Model Fit (χ^2/df)	RMSEA (CI)	TLI	CFI
A. Competitive Environment							
ET, CM, TA, CS, SP, IP	6	9	5.065	0.5627	047 (022.072)	0.942	0.933
B. Market for Products with cross loadings for Entry Timing							
MS, CA, RP, ET	4	2	1.273	0.6365	040 (015.065)	0.920	0.919
C. Agency Risk							
SE, IE, LE, TE	4	2	2.742	1.371	049 (022.76)	0.952	0.928

† No significant improvement in the modification indices (all the modification indices are less than 10).
‡ The abbreviations used for indicator variables are those shown in Table 1.

About the Authors

Brian L. DOS SANTOS holds the Frazier Family Chair in Computer Information Systems at University of Louisville's College of Business. He has been on graduate business school faculties at Purdue University, University of Wisconsin at Madison and Case Western Reserve University. His work on information technology investment justification and evaluation has been published in many of the leading archival journals in the field. Dr. Dos Santos has been engaged in a consulting capacity by a number of firms, including UPS, Motorola, Ameritech, Northern Telecom and Dow Elanco.

Pankaj C. PATEL is an assistant professor of management in the Miller College of Business at Ball State University. He received his PhD in entrepreneurship and strategy in 2009 from the University of Louisville. His work focuses on how entrepreneurial actions at micro and meso-levels translate to strategic and tactical outcomes at the venture level. His work has been published in *Journal of Operations Management*, *Journal of Economic Behavior and Organization*, *Human Resource Management*, *Strategic Entrepreneurship Journal*, *Entrepreneurship Theory and Practice*, and *Small Business Economics*.

Rodney R. D'SOUZA is an assistant professor of management and entrepreneurship at Northern Kentucky University. His research interests include opportunity identification, new venture teams, and early stage venture capital financing.