Uncovering Knowledge Structures of Venture Capital Investment Decision Making

A Working Paper

by

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Purpose

Entrepreneurs constantly seek capital for new and existing ventures although they face considerable constraints in obtaining financing. Venture capital from outside investors has been considered an important driver in the startup and growth of entrepreneurial firms. Understanding the specific investment criteria for venture capital funding is of foremost importance, since this may substantially improve these firms' chances of acquiring funding. The authors have chosen to predict funding by measuring the decisions on both funded and unfunded business plans.

Overall Findings

The study posits that venture capitalists (VCs) may be willing to fund a marginal team with better venture potential than a good venture team with limited venture potential. In other words, entrepreneurs need not only to assemble an effective team, but also to clearly demonstrate the venture potential of their proposed business. This finding contrasts with most prior studies, which identify the venture team as the key funding criterion.

Highlights

• The findings suggest that while a venture team's composition and ability are a minimum requirement in the consideration of a venture capital investment and a major factor in explaining why a business plan gets rejected, these features are not significant in explaining why a business plan gets funded.

• The study implies that venture potential is a better indicator of business plan funding than venture team quality and that VCs have similar knowledge structures and preferences when it comes to funding and not funding actual business plans.

• The researchers analyzed the relationship between rates of return and factors such as venture team quality and venture potential. The analysis finds that a good venture team has decreasing returns even for funded ventures, but favorable competitive conditions and market potential of a business plan have increasing returns.

Scope and Methodology

The authors of this study examined both funded and unfunded business plans to determine the key factors in the venture capital investment decision process. The 2004 sample originally consisted of 200 business plans from venture capitalists that had invested as individuals. Of these business plans, 72 were funded and 128 were not funded. To increase the reliability of the study and obtain equal sized samples, 72 of the 128 unfunded plans were randomly selected. Also, steps were taken to generalize and improve the understanding of the latent decision process used across the United States. This involved obtaining business plans from the East and West Coasts. In a control for industry, business plans only from high technology firms were examined for the year studied.

Analysis was performed in three steps. First, a set of attributes meaningful to VCs was identi-

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fied using an adapted version of free-listing and focus group sessions. Second, a group of experts was asked to evaluate a set of business plans using the identified attributes. Finally, a Bayesian model was used to measure the decision factors that were identified and to predict the VCs' decisions with respect to funding the business plans.

This report was peer reviewed consistent with the Office of Advocacy's data quality guidelines. More information on this process can be obtained by contacting the director of economic research at **advocacy@sba.gov** or (202) 205-6533.

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Abstract

Studies on venture capital (VC) investment decision using espoused criteria and utility aggregation methods have shown mixed results. Using a latent decision structures approach from psychological scaling literature, we reduce random and systematic biases arising from VC decision environment. In addition, we further address such biases using a combination of parametric and nonparametric techniques and practitioner specified decision criteria on 143 funded and nonfunded business plans. Compared to previous studies that have emphasized the central role of the venture team in obtaining funding, we find that (a) a good venture team is critical for not rejecting a business plan but is less critical for funding a business plan (b) a good venture team has decreasing returns even for funded ventures, but favorable competitive conditions and market potential have increasing returns.

Keywords: decision making, entrepreneurship, venture capital

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1. Introduction

The extant literature on venture capital (VC) funding has found mixed evidence on the relative importance of the venture team, the characteristics of the market, and the business model (Dubini 1989; Hall and Hofer 1993; Macmillan et al. 1985; Macmillan et al. 1987; Shepherd 1999; Tyebjee and Bruno 1984). These findings, however, have been inconsistent mainly due to the fact that: (1) Venture Capitalists (VCs) are often not aware of how they really make judgments (Hall et al. 1993; Zacharakis and Meyer 1998); (2) VCs are affected by high cognitive overloads in decision making due to uncertainty and ambiguity (Camerer and Johnson 1991; Shanteau 1992); (3) VCs suffer from cognitive biases (Shepherd et al. 2003); (4) the assumption that all VCs share similar understanding of the attributes used by researchers (Franke et al. 2006); and (5) researchers have an accurate understanding and knowledge of the number and nature of criteria used by the VCs.

To address the above issues, we start with no assumptions or impositions about the VC decision-making process. In addition, rather than using espoused criteria or hypothetical investment scenarios, we use a set of 143 funded and unfunded business plans for our analysis. We compile a list and the meanings of criteria used by VCs and analyze the role of these criteria on VC decision making using a set of parametric and nonparametric empirical approaches. While previous studies have analyzed VC decision processes through different theoretical lenses, our approach is focused more on knowledge elicitation and representation approaches to address key challenges in the decision making process germane to VCs. Using psychological scaling and expert systems literature, we focus on the nature and structural relationships among the attributes used in making funding decisions. Compared to typical approaches on understanding the nature of decision *processes* that may be fraught with idiosyncratic random or systematic decision errors, we focus on the nature of decision *structures*. Focusing on decision structures may facilitate identification of more stable funding criteria.

This article proceeds as follows. First, we review the literature on expertise and consider VCs to be experts in the realm of investment decision making. We then identify some drawbacks in previous research with regard to elicitation of VC decision making in the light of expertise literature. In the third section, we build our framework – relying on literature from expert knowledge structures to overcome problems associated with knowledge acquisition and representation germane to VC investment decisions. In the fourth section, we describe the data used in the study, followed by the methodologies used to corroborate our analysis framework. Prior literature has typically found the critical role of venture teams in VC funding decisions (Franke et al. 2006). Contrary to these findings, we find that (a) a bad team may definitely lead to nonfunding but a good team does not necessarily lead to funding (b) a good venture team has decreasing returns even for funded ventures, but favorable competitive conditions and market potential have increasing returns. In other words, a good team may be the threshold for being considered for funding but is not a sufficient condition for getting funded. Finally, we discuss the implications of these results for future entrepreneurship research as well as practice.

2. VC's Expertise and Decision Structures

VCs make decisions under conditions of uncertainty, vagueness, and subjectivity of starting a new venture. Such decision making environment may interfere with the power of expertise as seen in more stable domains. This fact does not reduce the critical nature of expertise under uncertainty (Zsambok and Klein 1996). The notion of uncertainty in expert literature is related to novelty creation (Ericsson et al. 1993; Ericsson and Smith 1991), high velocity of environmental change, and dynamic problem solving (Read et al. 2003). Research suggests that in time-critical and less structured [1] fields such as medicine and fire fighting, skilled expert performers produce superior actions when compared with their less skilled peers, even in situations where the individuals had no prior experience (Ericsson and Lehmann 1996). Under such conditions, organization and reasoning drive quick response without requiring justification for the solution (Patel et al. 1996). Therefore, we suggest that expertise in the VC industry could be accumulated in a way that is similar to how medical expertise is acquired and used in the face of uncertain diagnostic and emergency situations (Read et al. 2003). Such attributes (i.e. time-critical and lack of structure) seem highly applicable in the entrepreneurial environment. Empirical evidence of this exists in the case of VC decision making, wherein Shepherd, Zacharakis et al. (2003) explored Shanteau's (1992) ten attributes of tasks that allowed predictions as to whether expertise would improve or impair decision-making performance. Their findings suggest that growing expertise on the part of VC's should, in fact, lead to increments in their performance.

Further, the literature on expertise suggests that experts in a given task requiring decision-making, may show higher judgment accuracy (Dreyfuss and Dreyfuss 1986; Nosofsky 1986) and as a result, VCs may choose the "right" company more accurately as experience increases (Shepherd et al. 2003). However Rabin (1998) suggests that experts might be susceptible to inferring *too much from too little* information and misreading evidence. This puts experts at a particular risk because, as part of their acquisition of expertise, they may have become so mechanical that they *miss things*. These conditions worsen when the decision maker is placed in an environment characterized by high uncertainty, ambiguity, and incomplete and asymmetric information – characteristics of the environments VCs operate in. This may lead to ascribing

[1] The medical environment presents "ill structured problems, uncertain dynamic environments, shifting, ill-defined or competing goals, time stress and high risk as well as issues associated with multiple players" (Patel et al. 1996).

inappropriate weight to information cues and to making errors combining them (Camerer et al. 1991). Therefore, the decision environment poses significant challenges to understanding and analyzing decision criteria used by VCs in decision making. Researchers in expert systems literature suggest that while the decision process may be fraught with processes of random or systematic errors, understanding the nature and relationships among attributes for decision making is important. The following section addresses these shortcomings in the context of current approaches to understanding VC decision making, and explains how latent decision structures may provide more reliable and valid understanding of the VC decision process.

3. Previous Research on the VC Decision Process

In order to explore the drawbacks with previous research, it is necessary to understand the VC decision making process. In brief, a typical business plan goes through two stages in the decision making process – screening and due diligence (Sahlman 1990; Tyebjee et al. 1984). In the screening process, VCs evaluate whether a business plan deserves further interest. According to Sahlman (1990), almost 80 percent of the business plans are rejected in the screening process. Business plans that merit further attention undergo the due diligence process, during which venture characteristics are further scrutinized and venture team potential is judged. Often, VCs invest in syndicates and therefore make use of multiple due diligence processes. Additionally, prior research ignores the underlying heterogeneity among decision makers and assumes similar decision making challenges.

Research thus far suggests that conditions of VC decision making are neither structured nor unambiguous, and that the knowledge elicitation process and the eventual representation process pose significant challenges under conditions of VC decision making, due to the nature of available information, biases, and heterogeneity in decision making (Shepherd 1999; Zacharakis et al. 1998). The literature on expertise suggests that elicitation and aggregation techniques are factors for explaining a set of key investment parameters. This literature also suggests that knowledge acquisition and its representation from experts requires developing an understanding of the decision making process (Cooke and McDonald 1987).

Each of these is discussed in detail in light of previous studies. Specifically, the roles of interviewing and verbal protocol techniques in eliciting knowledge are discussed using a researcher-specified list of attributes or scenarios. It is suggested that techniques such as these may compromise knowledge elicitation either through the nature of tacit decision making or through researcher-defined decision criteria. Additionally, the knowledge representation approaches typically imposed by researchers are assessed. These knowledge representation approaches entail the use of empirical approaches that make assumptions about the knowledge representation which do not mesh with actual decision making. While prior research has discussed limitations of espoused criteria and verbal protocols (Franke et al. 2006), this study specifically focuses on widely used additive utility models (for example conjoint analysis) that makes assumptions that do not lend readily to VC decision making.

3.1 Knowledge Elicitation

The key hurdle in knowledge elicitation under VC decision making is that of necessity of introspection and verbal expression of tacit knowledge and decision processes. Worse yet, with increasing expertise, such elicitation is increasingly difficult (Johnson 1988). Prior research aimed at eliciting knowledge structures of VCs typically made use of a list of attributes that researchers suggest VCs utilize when investing in a particular venture. Such operationalizations have been typically analyzed using verbal protocols (Sandberg et al. 1988), ranking methods (Macmillan et al. 1985; Macmillan et al. 1987; Tyebjee et al. 1984), and in the last decade by using additive utility methods (Shepherd 1999; Shepherd and Zacharakis 1999; Shepherd et al. 1998; Shepherd et al. 2003; Zacharakis et al. 1998; Zacharakis and Meyer 2000; Zacharakis and Shepherd 2001).

The problem with using ranking methods and verbal protocols in knowledge elicitation is that introspection and verbal expression of knowledge are difficult tasks for experts. Additionally, research on the subject suggests that an expert's ability to express knowledge is inversely related to their experience (Johnson 1988). Experts may not accurately report mental states or mental processes through introspections (Cooke 1994, 1999; Hoffman et al. 1995). This is why when asked to provide explanations for their behavior, experts often produce reasons, rules, or strategies that do not correspond to their actual behavior (Rowe et al. 1996). Additionally, expert knowledge consists of automatic or compiled mental processes. Therefore, processes or strategies used by experts might not be available for introspection (Johnson 1967; Jonassen et al. 1993; Schvaneveldt et al. 1985; Shepard 1962a, 1962b; Shiffrin and Schneider 1977).

Further, Cooke and McDonald (1987) contend that even if experts could accurately *introspect* their decision process, they still face the problem of transferring that knowledge to the researcher as well as dealing with the subjective interpretation of the researcher. Typically a researcher is alien to a VC's domain and the VC is alien to the knowledge representation processes. The VC's decision process is observed or recorded, interpreted, transformed, and then analyzed through the researcher's analytical framework, making the representation of knowledge an artifact of the researcher's framework. In addition, VCs may not be able toexpress the mental processes while explaining the investment decision process to researchers.

3.2 Knowledge Representation

Literature suggests that expert knowledge consists of concepts, relations, features, chunks, plans, heuristics, theories, mental models, etc. However, one must find the means to create a closer representation so as to reduce mismatches. Cooke and McDonald (1987) suggest that "to avoid such a mismatch… knowledge representation of the system should be driven by a formal knowledge acquisition process which would reveal the contents and organization of expert knowledge." Typically, researchers analyzing elicited data impose theoretical or empirical constraints with regard to how knowledge is represented.

A researcher may impose theoretically borrowed relations that are empirically implemented. For example, empirical models may justify independent effects of the competitive environment, market, and teams, whereas VCs may not see the relationships in a similar vein. Irrespective of the approach, the goal must be to match an expert's knowledge representation with the analytical framework (Camerer et al. 1991). Additionally, experts differ considerably from novices' reasoning and knowledge structure. Imposing structures and processes based on general knowledge is inconsistent with highly knowledge-specific and tacit approaches used by VCs. This strongly suggests that the use of researcher-defined criteria in eliciting or imposing decision criteria is insufficient and inadequate.

Therefore, while literature has pointed out drawbacks of espoused criteria, verbal protocols, and cognitive biases (Franke et al. 2006; Shepherd et al. 2003), the currently accepted knowledge representation approach from additive utility models has limited application in understanding VC decision making. The key issue with applicability of conjoint analysis is the requirement of independence of attributes to implement assessment of independent scenarios (Green et al. 2001). However, the limitations of applicability of conjoint analysis are discussed in detail below.

First, one of the key assumptions of the technique is the addition of part worth utilities (Green et al. 2001). This assumes the inherent independence of attributes. Typically, in marketing, conjoint models are associated with products whose attributes are sharply distinct and hence uncorrelated (Green et al. 2001). In other words, changing the level of one attribute does not affect the level of other attributes. This is a strong assumption in the context of ventures, where much of the potential of a venture is endogenously determined. A better opportunity may result in a better competitive positioning and market potential, which in turn is highly correlated to better venture teams. Thus, the attributes of a business plan. Therefore, such dependence of utilities may not be strictly additive and may result in unstable estimates and poor predictions (Green et al. 2001; Huber et al. 1993). More important, scenarios presented to a decision maker in a conjoint experiment may not be assumed to be independent of the other scenarios.

Second, the greater the number of attributes to be assessed, the higher the cognitive load required on the part of decision makers. Additive utility models (e.g. conjoint analysis) require VCs to fill in for missing information for a given scenario. As in verbal protocol models, decision making is explored under hypothetical conditions (Shepherd 1999). While a researcher may eliminate redundant or nonsensical scenarios, the accuracy of judgments on the part of the decision maker is an artifact of a list of attributes developed by the researcher.

Third, these scenarios pose another problem in the way they are presented. They cause the participants to lose sight of the forest for the trees, to borrow from an old cliché. In other words, independent assessments of scenarios may result in overrating of certain features that may not be important to the overall picture. For example, analyzing scenarios based on market and team, and competitive advantage and team, may not result in similar assessments. Additionally, choice variables such as “low” or ”high” may have little value when the decision maker does not focus on the complete business plan. In reality, VCs make decisions of investing with the complete business plan in mind, and not focusing on individual parts. More important, under conditions of uncertainty and ambiguity, decision processes may be highly inconsistent, intransitive, and simply ambiguous (Zsambok et al. 1996). Therefore, decision making scenarios without complete business plans, assessed under high uncertainty, may result in reduced validity of assessments of participants.

Finally, conjoint analysis does not put constraints on the shape of the utility function (Green et al. 2001; Green and Srinivasan 1990). While this may be a useful approach, typical scaling algorithms use a shape function that is less subject to random errors that could arise from the decision maker's perspective.

Other issues with using conjoint approaches in VC decision making are: (1) from a socio-psychological perspective, VCs do not take decision making as seriously under these conditions as they would when deciding on real investment decisions, and (2) as all VCs would prefer ventures with high market potential and experienced and capable teams, there could be a lack of reliability and validity in the VC judgment (Shanteau 1992; Tversky and Kahneman 1974). Additionally, research suggests that considering the structural aspect of utility as fully defined in an environment with limited information is unadvisable (Blaszczynski et al. 1997; Nakamura 1996; Parsons 1996; Pawlak 1999; Slowinski 1993; Slowinski and Stefanowski 1993, 1996). These utility models could lead to the creation of cognitive biases that in turn increase the criticality of the stochastic component, which in turn could limit the provision of psychometric correction, beyond the obvious limitations of espoused criteria (Bishop and Heberlein 1990; Cameron and Huppert 1989; Diamond and Hausman 1994; Manski 2005; McFadden 1994, 1999). This suggests that most research to date has constrained the knowledge acquisition process by pre-selecting the knowledge representation process.

3.3 Formal Strategies for Knowledge Acquisition and Representation

Given the challenges with assumptions and implementations on the part of expert processes and analytical artifacts, literature on scaling techniques from cognitive psychology may be helpful, as it focuses on the information processing paradigm. More specifically, these methods focus on empirical findings in language, perception, memory, and problem solving to study representations of frames, scripts, features, propositions, and production systems (McFadden 1994). Psychological scaling algorithms empirically generate specific types of knowledge representations (e.g., spatial, hierarchical, network) (Cooke and McDonald, 1987). These techniques (specifically multidimensional/psychological scaling) combine elicitation and structuring aspects, and are more useful than traditional interview- or scenario-based knowledge elicitation techniques (Preston et al. 2005). They are also useful in the conceptual and refinement stages of the knowledge acquisition process. More important, research has found that scaling based elicitation techniques perform better than protocol analysis and interviewing (Burton et al. 1987), and addresses the typical drawbacks of conjoint analysis (Huber et al. 1993).

These psychological scaling techniques involve experts rating the similarity of different objects (usually chosen beforehand), followed by representing the rating as a distance on a scale, ranging from not similar to completely similar – the goal being the discovery of a rank order of objects within a problem domain. MDS developed by Kruskal (1977) is based on the use of the least squares method to fit the elicited data. Therefore while conjoint experiments may help elicit knowledge and the relative importance of espoused criteria, the researcher substitutes aggregation statistically because the nature of the combination of scenarios increases exponentially.

Additionally, MDS does not make any distributional assumptions about the underlying data, and given the heterogeneous nature of decision making and knowledge structures of the VCs, this is very important. Also, traditional techniques based on statistical representation are inherently unstable and the representations of knowledge may change with assumptions and processes of underlying technique. Finally, MDS provides an intuitive understanding to the practitioners without substituting their intuitions with the findings.

4. Methodology

The analysis was conducted in three steps. First, a set of attributes, as well as what they meant to the VCs, was identified using an adapted version of free-listing and focus group sessions. Second, using the identified attributes, a group of experts were asked to evaluate a set of business plans (all of which were either funded or rejected by VCs). These industry experts evaluated the business plans based on an understanding of common meanings of business plan attributes provided to them. Industry experts were used

,as they could provide a more objective assessment than asking VCs to re-evaluate their investments, which could lead to retrospective and attribution biases. The experts were not aware of which plans were funded and which were not funded by the VCs. Third, based on the evaluations by the experts, MDS was used to identify knowledge structures, followed by PRO-FIT and QDA to validate the key dimensions identified through MDS. To further ensure that our analysis was not an artifact of the parametric methods, AUTOCLASS (Bayesian mixture models) was used.

5. Data

The sample originally consisted of 200 business plans obtained from VCs, of which 72 were funded and 128 were not funded. In order to improve generalizability and understanding of common latent structures across VCs in the US, business plans were obtained from VC firms on the east and west coasts of the US. Further, to reduce heterogeneity across industries, only business plans from firms in the high tech industry who were seeking start-up funding during the year 2004 were considered. Given the fact that the experts are aware of the high rates of rejection of business plans, they could randomly not fund a large number of business plans and still make statistically correct predictions. Therefore in order to increase the reliability of the study, 72 of the 128 non funded business plans were randomly chosen. Evenly distributing the business plans enabled the elimination of chance predictions by the experts.[2] Therefore, the final dataset consisted of 144 business plans, of which 72 were funded and 72 were not funded by VCs. To ensure that decision processes were independent, only business plans that VCs had invested in as individuals, as opposed to investment via syndication, were considered.

Data concerning the attributes used by VCs were collected by way of an adapted version of free-listing using 58 participants, who included VCs, angel investors, and commercial lenders, and two focus group sessions using 12 VCs and 15 VCs, respectively, from metropolitans areas in the midwestern United States. The free-listing and focus group part of our study is described below.

[2] To our knowledge there were no industry shocks to bias expert evaluations in 2004 and 2005, and because much of the funding was for startups, it is highly unlikely that startups were successful within a year to bias the expert's knowledge about potential of a product or service.

5.1 Identifying common meanings

The first step was to identify criteria that VCs use in making funding decisions. Towards this end, data were gathered from VCs, angel investors, and commercial lenders. The individuals were approached at a venture club meeting at a midwestern US city, and asked to participate. A modified form of the free-listing data collection technique was used, wherein respondents were asked a question about a particular domain and were invited to respond with a list of answers that represent pertinent elements in that domain (Weller and Romney 1988). Free-listing is recommended when little is known about a domain because it allows participants to provide information without researcher bias (Weller et al. 1988). The free-listing technique presents problems if different individuals have different definitions for the same term, or if different respondents use the same term, but have different meanings. To avoid this problem, 22 criteria were identified that prior literature in strategy, finance, and sociology found to play an important role in the success of business ventures, as well as criteria suggested by the popular press. Examples of criteria included potential market share (Schmalensee 1981), revolutionary nature of product/service (Aaker and Day 1986; Williamson 1985), use of technology (Aaker et al. 1986), timing of the new venture (Aaker et al. 1986; Mitchell 1991), competitive advantage (Robinson and Fornell 1985; Schmalensee 1981), value added by the product/service (Andrews 1987; Shepherd 1999), ability to attract and retain customers (Robinson et al. 1985; Schmalensee 1981), soundness of business model (Chatterjee 1998), ability to protect intellectual property (Golder and Tellis 1993), product life (Golder et al. 1993), communication skills, clear and realistic funding needs, potential for profitability, networks/contacts, potential for growth, flexibility (willingness to change), and management experience (Hannan and Freeman 1989; Stinchcombe 1965).

This list of terms with definitions for each term was distributed to the 120 participants, who were asked to identify the criteria they used to determine whether they would invest in a new business. Fifty-eight responses were received. Generally, 20 to 30 respondents are recommended to get a complete picture using the free-listing technique (Weller et al. 1988). Respondents were also asked to list any criteria that were not part of the list provided to them and explain what they meant by any added criteria, and to rank the criteria in their lists in terms of their importance. Six new criteria were added by respondents, giving us a total of 28 criteria. From the 28 criteria provided by the participants and their rankings, seven criteria were eliminated because they appeared on few lists and were ranked very low. This gave rise to a list of 21 criteria.

This set of 21 criteria was presented to a focus group of 12 individuals that included venture capitalists and angel investors (both institutional and private) from a midwestern US city. These 12 individuals were contacted through the researchers' personal contacts and asked to participate in the study. Cumulatively, the participants in this group were the lead investors in over fifty different businesses. The purpose of this focus group was to 1) determine whether the terms and definitions used earlier 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.

Finally, the categories and the criteria within each category, along with the definitions for each criterion, were presented to another focus group of 15 VCs from a different midwestern US city. These individuals were also contacted through the researchers' personal contacts and asked to participate in the study. This group was used to validate/change the criteria and scales, and to determine how important each category was in their funding decisions. The data gathered in this stage, together with the data gathered from the previous focus group, were used to weight the different criteria that are important in the VC decision-making process.

5.2 Expert Evaluation

The purpose of this stage was to determine how well each of the plans did on the criteria identified in the first stage. Towards this end, nine experts were asked to evaluate the business plans. The experts were individuals from a midwestern city in the US. On average, they had 18 years of experience in dealing with VC funding in the high tech sector. Each of the 72 funded business plans was evaluated three times, and 71[3] of the unfunded business plans were evaluated three times. As one of the unfunded business plans did not receive three evaluations, it was taken out of the analysis, leaving us with 72 funded business plans and 71 unfunded

[3] Two experts did not provide complete evaluation of the unfunded business plan, thus the final sample consisted of 72 funded and 71 non-funded business plans.

business plans. Each expert evaluated an average of two plans per week over a 23-week period in 2005 using the criteria established in the first stage.[4] In addition to rating each plan on the established criteria, each expert was asked to indicate whether a plan should be funded. After expert evaluation, seven out of these 21 criteria were removed from the analysis as they pertained to presentation quality of the business plan, types of financial documentation, and funding milestones. The final set of criteria are startup experience, industry experience, leadership experience, management experience, market size, customer adoption, revenue generated, entry timing, competition, technological advantage, strategy, intellectual property rights, value added, and profit margins.

6. Analytical Approach

A synopsis of the data analysis approach can be seen in figure 1 below. Given the nature and structure of decision making, a latent structure confirmed by multidimensional scaling (MDS) and AUTOCLASS was developed. Both of these techniques do not make assumptions about the underlying distribution of the data.[5] First, the nature of underlying attributes for a given venture using MDS was identified. To create confirmatory and more deductive inferences from the identified structure, the linear PRO-FIT and nonlinear QDA techniques were used to identify relative importance of attributes identified through MDS. Finally, even though MDS and PRO-FIT explain substantial variance, there is a possibility that heterogeneity[6] exists among the VCs latent structure in preferences when it comes to funding plans, but

[4] 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.

[5] Assumption of the underlying distribution is critical to understand the latent structure because of the potential of underlying heterogeneity at the individual decision level and VC firm level. Ventures invested in are heterogeneous in nature in terms of industry potential and other external dimensions.

[6] Many latent class MDS techniques have been identified in marketing Sinha and DeSarbo (1988) However, these techniques are based on market segments of consumers that may not be easily discernible in the case of the VC industry. Moreover, VC syndicate networks may mean that segmentation among VC firms may not be as distinct as possible. The cross interaction of the nature of venture under consideration may increase

as these inferences are based on parametric methods, it is likely that VCs who depend on their ability to manage market and agency risk would pick business plans accordingly. This is where the Bayesian unsupervised model, AUTOCLASS, comes into play, as it may help address some possible shortcomings of parametric approaches, and further enhance methodological convergence and inference validity. AUTOCLASS models the data as a mixture of conditionally independent classes. Advantages of using Bayesian unsupervised models include: (1) they are parameter-free, (2) user input is not required, (3) prior distributions of the model offer a theoretically justifiable method for affecting the model construction, (4) these models work with probabilities and can hence be expected to produce smooth and robust visualizations with discrete data containing nominal and ordinal attributes and (5) the Bayesian approach has no limit for minimum sample size (Kontkanen et al., 2000). A quick overview of the analysis is presented in Figure 1 below, starting with parametric methods.

INSERT FIGURE 1 ABOUT HERE
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7. Results

Furthermore, adequate power was found with the proposed techniques. For two dimensions identified with MDS, the sample size falls within recommendations from Carroll and Arabie (1980). Also, as mentioned earlier, high levels of reliability across experts in discriminating funded and nonfunded business plans indicates high effect sizes of the set of attributes. Thus, considering average effect size of 0.5 and α=0.05, with a sample size of 143, power is substantially high (β>0.9). Furthermore, such high power means that results of nonlinear discriminant analysis will be more reliable. Similarly, for unsupervised Bayesian classification, the minimal sample size issue is not critical (Kontkanen et al. 2000a; Kontkanen et al. 2000b). However, sizes of 58 and 143 are more than adequate (Raudys and Jain 1991).

The degree of agreement among experts' business plan evaluations was assessed, and the inter-rater reliability among experts using attributes identified by VCs on funded and unfunded business plans was 0.93,

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heterogeneity but it may not be as discrete as a market segment in marketing. However, it is necessary to control for such heterogeneity.

suggesting high inter-rater reliability. Additionally, the difference between funded and nonfunded business plans based on expert ratings was significant ($p<0.015$). Logistic regression using expert ratings explained 89 percent of the variance between funded and nonfunded business plans. To further confirm the degree of matching between experts and actual decisions, a composite score was created using principal component analysis. The reliability for expert loadings was 0.94.

The first decision in MDS is the choice of number of dimensions that capture the underlying latent structure. A typical statistical program gives a range between one and six. However, choosing a number in between the range provided by the software is ad hoc, and certain important dimensions could be missed, if more than six dimensions are required. In this case, the similarity matrix was first subject to principal components analysis (PCA). The first three components accounted for 94.78 percent of the variance – the first component 54.71 percent, the second component 33.54 percent, and the third component 6.53 percent. Thus, three dimensions would be sufficient to describe the data. Based on previous studies and as recommended by Kruskal and Wish (1978), Young's stress formula was used, and the stress was found to be least (stress = 0.061) for two dimensions. Additionally, the reduction in stress with increased dimensions is minimal. Furthermore, the minimal variation identified by the third component of the PCA supports the inference that <u>two dimensions are adequate to represent the decision structure.</u>

Figure 2 below shows the spatial distribution of funded and nonfunded business plans. The fact that the funded business plans fall toward the left side of the graph suggests that the first dimension is an important indicator in signifying funding criteria. Based on Ohlson (1980), two logit analyses were considered as the ability of dimensions to differentiate between funded and nonfunded business plans. First a traditional logit was considered, with dependent variable as funded (1) and nonfunded (0) business plans. Based on this analysis, the first two dimensions were found to be significant at the 0.95 level. This mapping also suggests that two dimensions are sufficient for appropriate representations.

INSERT FIGURE 2 ABOUT HERE

MDS analysis focused on the creation of a map wherein it can be seen that funded business plans differ from nonfunded business plans. Understanding the results above, however, requires the use of PRO-FIT[7]. PRO-FIT is a regression-based technique that explains the degree to which a given level of an attribute is associated with a business plan. The results are represented graphically in Figure 3 below. Due to space restrictions, all the diagnostic statistics are not reported. Most of the cases had an R^2 greater than 0.9. For each of the 14 attributes used, a line is drawn through the space such that the value of the attribute increases with direction of the line. The attributes that load on the horizontal axis shows that dimension one is associated with the <u>competitive environment</u> (the horizontal axis), and the attributes that load on the vertical axis show that the second dimension is associated with the <u>characteristics of the founding team</u> (the vertical axis). These lines indicate that the competitive environment is the most important indicator of funding and nonfunding decisions.

INSERT FIGURE 3 ABOUT HERE

Next, as suggested by Richardson and Davidson (1984), there may be a statistical inference problem if the variance-covariance matrices are different. While this is more applicable in discriminant analysis, in the case of logit analysis, nonlinear terms must be included in the analysis (Mar-Molinero and Ezzamel 1991; Mar-Molinero 1988). Using a general linear model, a saturated model with quadratic and interaction terms was used and later simplified using standard procedures outlined by Dobson (2002). It was inferred that the square of the second coordinate was a necessary dimension to capture richness of the data. Therefore, probabilities for funding could be calculated, while other points in the space are occupied by hypothetical business plans (Mar-Molinero et al. 1991), and every point in the space could be allocated a probability of funding. Points in the space with the same probability of funding could be joined to create an *iso-nonfunding*

[7] Based on popular recommendation Borgatti (1996, 1998) and Carroll and Chang (1969) and the nature of attribute scale we use metric PRO-FIT approach, wherein a set of multiple regressions are run using dependent variable (each attribute), and independent variables at each point in space.

surface. This suggests that even though there is no simple discriminating frontier between funded and nonfunded business plans, one may use a set of discriminating frontiers with different probabilities. Therefore using a set ranging from 1.0 to 0.25 in the increments of 0.25, the 0.5 iso-line is the discriminant.[8] This model (the best discriminatory model) misclassifies only 9 business plans out of 143 (four funded and five unfunded business plans were misclassified; misclassification rate of 6.3 percent). This can be seen in figure 4 below, wherein the 0.5 curve correctly classifies 93.7 percent of the business plans.

INSERT FIGURE 4 ABOUT HERE

Therefore, based on QDA and PRO-FIT, it can be inferred that there are two key dimensions – competitive environment and founding team. However, the nonlinear nature of the founding team suggests that venture team characteristics are important to a certain extent, after which this effect declines. Thus, having a better team has decreasing returns. Finally, the degree of heterogeneity in VC funding is assessed using a distribution-free inference technique, AUTOCLASS,[9] which requires no class imposition on the part of the researcher.

As seen in Table 1(a) below, AUTOCLASS also indicates that two distinct clusters exist. The class weight of 77 unfunded and 66 funded is very close to the original 71 unfunded and 72 funded. Therefore, heterogeneity is assessed for funded and nonfunded business plans. The results in Table 1(b) show 12 of the 14 criteria important for differentiating the two groups. More important, results from table 1(b) suggest that management team, industry experience, startup experience, value added, market size, competition, timing, technology, IP, harvest potential, leadership/CEO experience, and strategy (listed in their order of importance) are criteria utilized by VCs when not funding a business plan. High class strength (Cheeseman and Stutz 1996) suggests that there is negligible heterogeneity among VC firms in funding and nonfunding. Therefore, factors leading to heterogeneity are not explored.

[8] This approach is widely accepted and used in the finance literature predicting failure

[9] http://ic.arc.nasa.gov/ic/projects/bayes-group/autoclass/

INSERT TABLE 1(a) and 1(b) ABOUT HERE
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8. Discussion and Implications

First, contrary to previous studies on VC investment decisions that focused mainly on espoused criteria, this study focuses on funding criteria, trying to replicate latent investment preferences of VCs (using real business plans), and provides a more contingent view to the VC investment decision process. The findings explain the prior research in terms of the importance of a team and go further by explaining that VCs use the competitive environment more intensely, while the venture team, though important, is of limited help beyond a certain extent. This suggests that team composition is a major factor in explaining why a business plan gets rejected, but is not significant in explaining why a business plan gets funded**.** This finding therefore contrasts with most prior studies, which identify venture team as the key funding criteria, and goes against the popular notion that suggests that an *A team and B opportunity beats a B team and an A opportunity*. The findings also suggest that teams have a decreasing return to scale. Previous research regarding the relationship between characteristics of the founding team and team effectiveness is inconsistent and inconclusive (Norburn 1986; Norburn and Birley 1988; O'Reilly et al. 1993). These findings lead Priem (1990) to propose a curvilinear relationship between the characteristics of the top management team and venture performance (Pettigrew 1992). Shepherd (1999) found that VCs' assessment policies of new venture survival were in fact consistent with those that literature suggested would increase the survival chances of the firm. Therefore, even though the findings are surprising, they are exactly in line with what Priem (1990) had proposed as to the curvilinear relationship between team composition and the VC investment decision.

Second, by presenting alternative methodologies to understand the latent structure of VC knowledge structure, the current study provides alternative approaches for future researchers who wish to study repeat entrepreneurs. In contexts where it is difficult to explicitly explain the thought and decision processes (e.g. entrepreneurial contexts), using MDS in conjunction with other confirmatory practices may be useful in eliciting knowledge and decision structures. Understanding such knowledge structures has great implications for pedagogy and entrepreneurs alike. Also, the homogeneity in the process of decision making may indicate the syndication effect on VC decision making. An increased number of investments made in syndicates, and high levels of network associated with creating value in investments, may result in substantial development of a common outlook. This is substantiated by the high levels of homogeneity in VC decision making for funded and nonfunded ventures.

Finally, from a practical standpoint, entrepreneurs face substantial constraints in obtaining finance and therefore understanding specific investment criteria is of paramount importance. Understanding criteria for funding may substantially improve their odds of funding. Based on the findings in this paper, entrepreneurs need not only to assemble an effective team, but also need to clearly demonstrate the venture potential of their business venture. From a pedagogical point of view, teachers can help students (potential entrepreneurs) understand fundamental VC decision criteria, and show them how matching their characteristics with VC investment criteria could assist them in their efforts of obtaining financing for their ventures. These findings present a specific challenge to pedagogy in terms of long-held beliefs about the importance of venture teams. Therefore, for teachers an increased challenge is to teach students how to correctly identify and position ventures to reflect the future potential of the venture.

9. Limitations

Like any study, this one is not without its limitations. First, even though evaluations by experts demonstrated high reliability, the investment process undertaken by VCs is complex and drawn out. Thorough due diligence and interactions between VCs and teams are not considered. However, focusing on the final decisions may help shunt the decision process, because outsiders cannot control or affect the decision process. Thus, focusing on key criteria that lead to investment may be more useful to entrepreneurs. Secondly, although the analytical framework helps provide convergence, the data come from a narrow time frame from one industry. Thus the generalizability of the findings may be limited. However, given the changing knowledge structures over time, not only the nature attributes, but the relative weights may also change. Therefore, to remove the effects of heterogeneity over time and across VCs, a narrow time frame of data is necessary.

Finally, because the entire investment process was not closely monitored, the issue of equifinality in decision making may be at play. In other words, VCs may have reached the same decisions through many different criteria and attributes. Thus, identified criteria from one group of VCs may not be applicable to others. This was partially controlled for by using a set of multiple statistical techniques with a different set of assumptions. Similarly, the high discriminatory power of expert assessment with VC investment decision explains why the set of attributes may actually be relevant in decision making.

Overall, based on all the analyses, it can be inferred that (1) venture potential is a better indicator of funding than venture team; (2) while venture team has decreasing returns, it is a potential deal breaker for not getting funded; and (3) VCs have similar knowledge structures and preferences when it comes to funding and not funding actual business plans. In other words, VCs may be more willing to fund a marginal team with better venture potential than a good team with limited venture potential.

10. Conclusion

Using a framework for expert knowledge structures, a set of attributes most critical to VC investment decision making were identified. The paper adds to the current literature by deriving a set of attributes that are widely accepted in the VC decision-making process, rather than provide vague attributes such as market potential. The results suggest that market factors are most important in determining whether a business does receive VC funding, and the quality of the management team is most important in determining whether a business does not receive funding. More important, compared with previous research it provides a more contingent view to the VC investment decision process. Even though the venture team ability is a minimum requirement and a venture may not get funded if the team is not qualified, this qualification is a prerequisite for considering venture potential. VCs are willing to accept a marginal team if the venture potential is high, but the prime reason for not funding is the lack of an appropriate team.

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Figure 1: Analytical Techniques

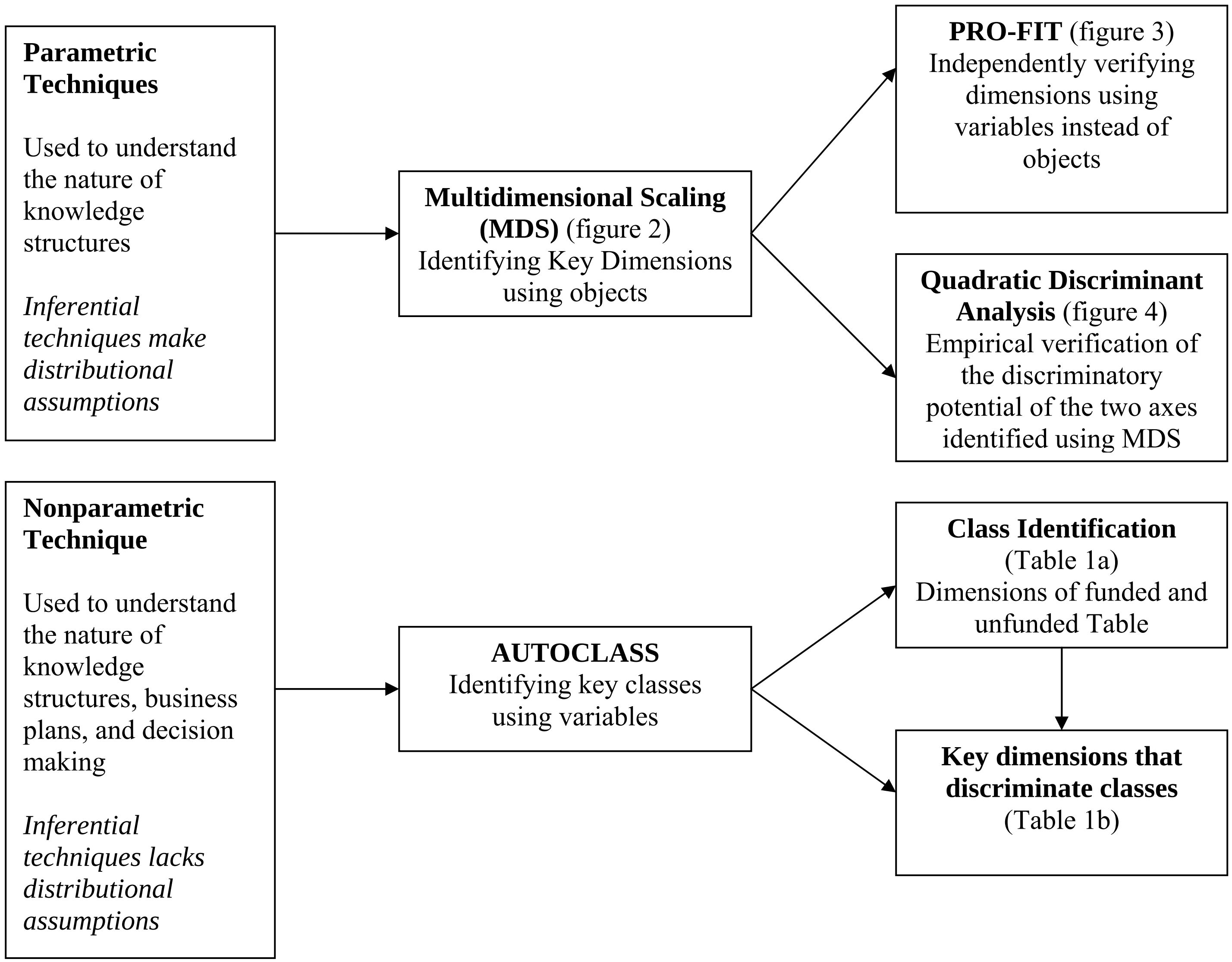

Figure 2: MDS Analysis

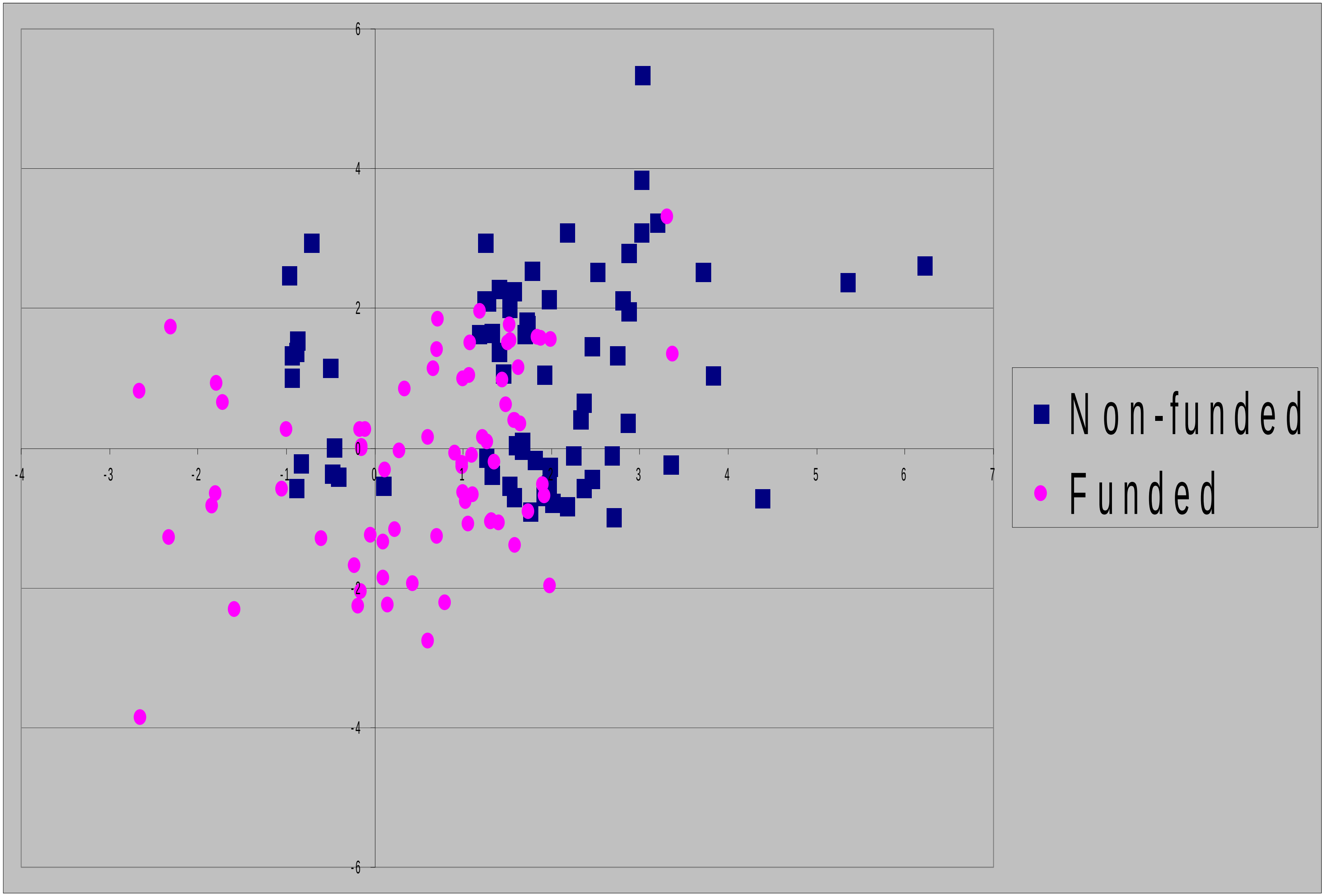

Figure 3: PRO-FIT Analysis

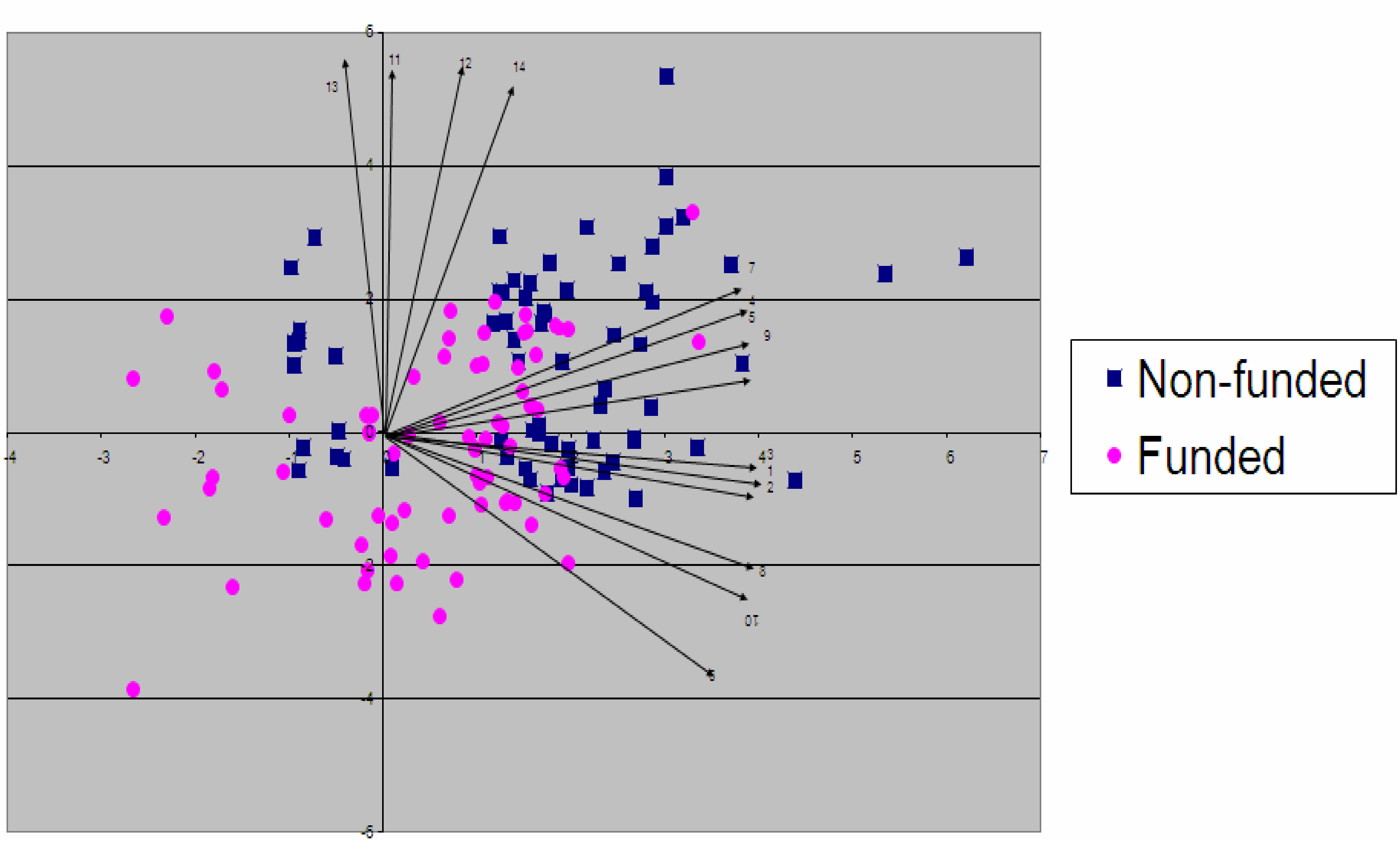

Figure 4: Quadratic Discriminant Analysis

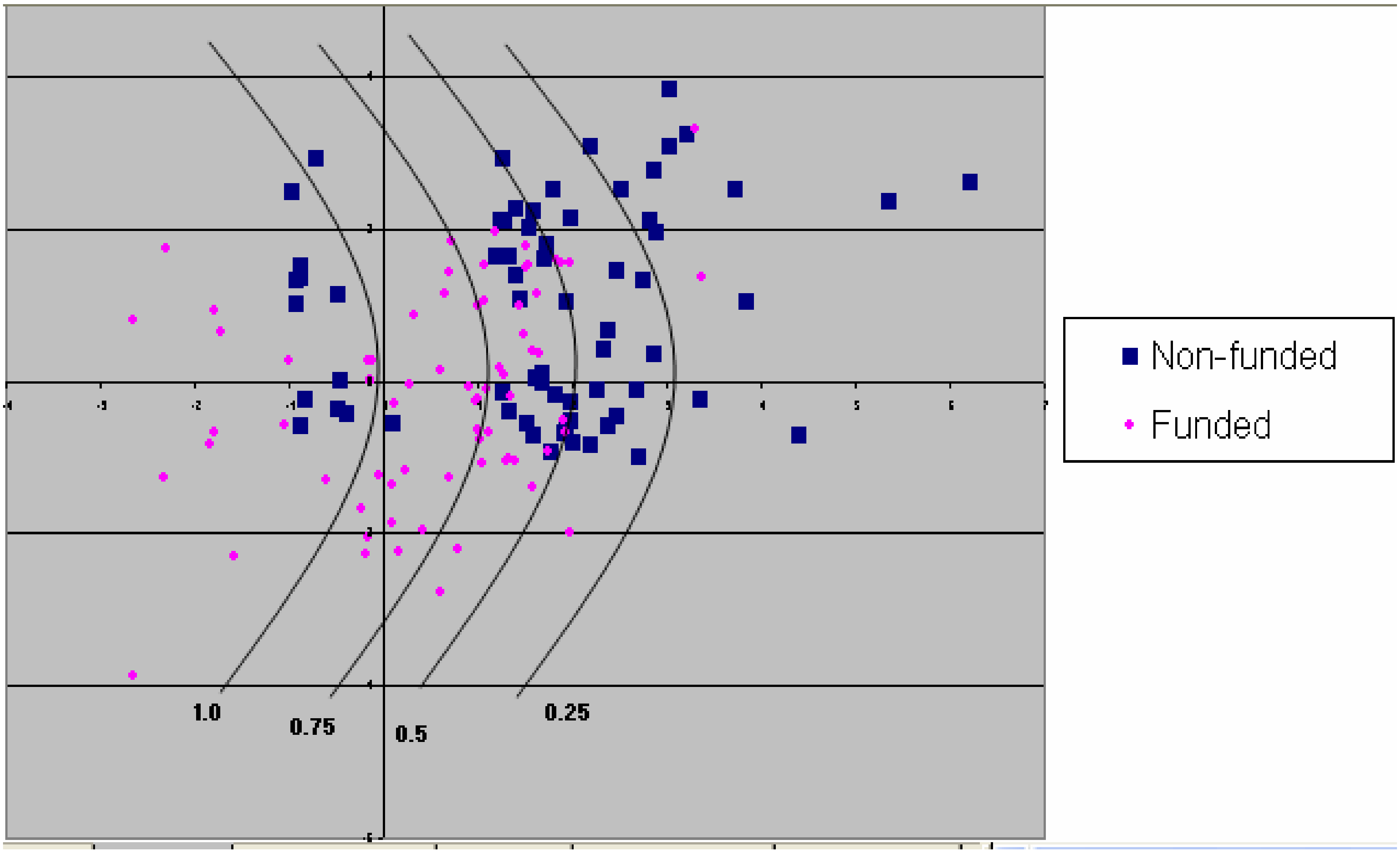

Table 1: AUTOCLASS Results

Table 1(a) Class Strength[10]

Class #	Log of class strength	Relative Class Strength	Class Wt.	Normalized Class weight
0	-42.1	1.00	77	0.54
1	-50.3	0.67	66	0.46

(real distribution is: 72 funded + 71 not funded)

Table 1(b): Within class attribute measures

Attribute	**I-jk** [11]	**Attribute**	**I-jk**
Group 0 (nonfunded business plans)		Group 1 (funded business plans)	
Management Experience	2.31	Value Added	3.01
Industry Experience	2.16	Market Size	2.97
Startup Experience	2.11	Competition	2.71
Value Added	2.08	Entry Timing	2.57
Market Size	2.05	Technology	2.40
Competition	2.01	Technological advantage	2.36
Entry Timing	1.98	Strategy	2.25
Technological advantage	1.76	Startup Experience	1.88
Intellectual Property Rights	1.47	Industry Experience	1.76
Harvest Potential	1.21	Leadership Experience	1.69
Leadership Experience	1.07	Management Experience	1.67
Strategy	1.04	Harvest Potential	1.32
Class entropy with respect to global entropy	8.47		9.23

[10] The class divergence, or cross entropy with respect to the single class Classification, is a measure of how strongly the class probability distribution function differs from that of the database as a whole. It is zero for identical distributions, going infinite when two discrete distributions place probability 1 on differing values of the same attribute.

[11] I-jk denotes the term influence value for attribute k in class j. This is the cross entropy or Kullback-Leibler distance between the class and full database probability distributions