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Venture Capitalists' Evaluations of Start-Up Teams: Trade-Offs, Knock-Out Criteria, and the Impact of VC Experience

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The start-up team plays a key role in venture capitalists' evaluations of venture proposals. Our findings go beyond existing research, first by providing a detailed exploration of VCs' team evaluation criteria, and second by investigating the moderator variable of VC experience. Our results reveal utility trade-offs between team characteristics and thus provide answers to questions such as "What strength does it take to compensate for a weakness in characteristic A?" Moreover, our analysis reveals that novice VCs tend to focus on the qualifications of individual team members, while experienced VCs focus more on team cohesion. Data were obtained in a conjoint experiment with 51 professionals in VC firms and analyzed using discrete choice econometric models.

Introduction

Research into the criteria venture capitalists use to assess venture proposals began in the 1970s and has been of constant interest to scholars until the present (Franke, Gruber, Harhoff, & Henkel, 2006; MacMillan, Siegel, & Subba Narasimha, 1985; MacMillan, Zemann, & Subbanarasimha, 1987; Muzyka, Birley, & Leleux, 1996; Poindexter, 1976; Shepherd, 1999; Tyebjee & Bruno, 1984; Wells, 1974). Three reasons seem to explain the strong interest that this field of research has attracted. First, knowledge on VC evaluation criteria helps those seeking funds to better judge their own venture project and to avoid potential flaws in their proposals. Second, the findings provide members of the VC community with an aggregate view of the evaluation criteria in use and with an empirical basis for comparing their own judgment to that of their peers. And third, as VCs are

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considered experts in identifying promising new ventures, their evaluation criteria are often interpreted as success factors for emerging firms (Riquelme & Rickards, 1992; Shepherd & Zacharakis, 2002).

The evaluation of venture proposals is one of the key activities of VCs. Previous studies indicate that VCs use various criteria to assess the attractiveness of venture projects, such as market growth and size, product offerings, the expected rate of return, and the expected risk of a venture project (MacMillan et al., 1985; Tyebjee & Bruno, 1981). Prior research also shows that among the set of evaluation criteria, VCs place particular importance on criteria related to the start-up team (Díaz de León & Guild, 2003; Gorman & Sahlman, 1989; Muzyka et al., 1996; Poindexter, 1976; Shepherd, 1999; Silva, 2004; Smart, 1999; Tyebjee & Bruno, 1981; Wells, 1974; Zopounidis, 1994). As a popular saying in the VC industry highlights, VCs would rather invest "in a grade A team with a grade B idea than in a grade B team with a grade A idea" (cf. Bygrave, 1997).

Although the qualifications of the start-up team play a major role in VCs' evaluations, knowledge of the criteria used in team evaluations remains on a fairly general level. This is largely due to the fact that most prior studies investigate the evaluation of *complete venture proposals* and thus provide aggregate criteria rankings such as (1) technical education, (2) new venture experience, and (3) focus strategy (e.g., Shrader et al., 1997). Whereas such results are important to obtain an overall understanding of VCs' evaluations of venture proposals, they are necessarily limited in the depth of insight they can offer on team evaluations. Specifically, the existing results do not yet provide information on the importance of different parameter values for particular team characteristics. For example, if new venture experience is an important criterion, is it desirable that all team members possess such experience? Moreover, the existing results cannot reveal utility trade-offs among different team characteristics. If a team lacks industry experience, which potential strengths may compensate for such a shortcoming? Can it be offset at all, or are shortcomings in this regard a potential knock-out criterion? Hence, a more detailed understanding of team evaluation criteria is required.

Recent research by Shepherd, Zacharakis, and Baron (2003) suggests a second important extension to prior scholarly work on VC evaluation criteria. Drawing on cognitive theory, these authors find that the *experience of VCs* has a significant influence on their decision making. Because the assessment of team quality plays an important role in VCs' decision making, the evaluation of start-up teams may also be subject to experience effects. Prior research has not yet addressed this question, although knowledge on the existence and direction of any experience effects would be crucial to theory development on VC decision making, to the design of future research studies, and also to VC practice and venture teams.

Against this backdrop, the purpose of this study is twofold: First, we seek to provide a more detailed exploration of VCs' evaluations of start-up team characteristics, and second, we explore whether novice and experienced VCs attach differing importance to these criteria. We apply a conjoint approach that allows an experimental variation of team characteristics. Prior research suggests that conjoint analysis is particularly suitable for research on VCs' decision making (Shepherd & Zacharakis, 1999) as it yields more valid results than the more frequently used *post hoc* methodologies (e.g., questionnaires using Likert-type scales). Our sample consists of 51 VCs who were asked to rank 20 teams described in terms of seven characteristics. We analyze the rankings with discrete choice econometric models.

This paper proceeds as follows: In the next section, we review prior studies on the criteria used by VCs when evaluating start-up teams and draw on cognitive theory to argue why VC experience could be an important moderator variable. We then provide an overview of the conjoint research design used in this study and present our empirical findings. We conclude by outlining the implications of our results for research and practice.

Review of Prior Research

Criteria Used by VCs to Evaluate Start-Up Teams

As mentioned in the previous section, research into the criteria VCs use to assess venture proposals has a relatively long tradition. Yet the more specific question of "How do VCs evaluate start-up teams?"—which could provide more detailed insights—has received only little attention to date, leading scholars to call for focused research on VCs' evaluations of start-up teams (Siegel, Siegel, & MacMillan, 1993; Timmons & Sapienza, 1992). We briefly discuss the results of key studies investigating VCs' evaluations of venture proposals and distill their findings on those criteria that are related to the evaluation of start-up teams.

Table 1 provides an overview of prior research into the criteria VCs employ when assessing venture proposals. In this context, two observations seem to be noteworthy. First, the table shows that a wide variety of evaluation criteria have been suggested by the literature. In essence, however, it seems that they can be collated into four major groups, namely evaluation criteria related to (1) the product/service offering; (2) the market/industry; (3) the start-up team; and (4) the financial returns to be expected from the new firm. This observation is mirrored in the findings of Tyebjee and Bruno (1984), one of the most widely cited works in this area, which identified five basic evaluation criteria used by VCs: market attractiveness, product differentiation, managerial capabilities, environmental threat resistance, and cash-out potential.

Second, we see that—although the existing results are somewhat heterogeneous—VCs consistently rank criteria related to the start-up team among the top three evaluation criteria. This result is already evident in the pioneering study by Wells (1974), who found that management commitment, products, and markets were the key evaluation criteria in the VC decision-making process. The results from the large number of studies that followed show that at least one, but often two or even all three of the top-ranked criteria pertained to characteristics of the start-up team. For example, Muzyka et al. (1996) find that (1) the leadership potential of the lead entrepreneur; (2) the leadership potential of the management team; and (3) the recognized industry expertise in the team were most important in VCs' evaluations of venture proposals. MacMillan et al. (1985) also investigated criteria that would disqualify a venture proposal. Again, the quality of the start-up team was key, as 5 of the 10 most frequently rated criteria were related to the human capital base of the venture. The most recent findings stem from a field study by Silva (2004), which did not provide an explicit ranking of criteria yet highlighted the fact that the attention of VCs is heavily focused on assessing the quality of the start-up team.

The available evidence thus indicates that evaluation criteria related to the start-up team are of major importance in VCs' decision making. More specifically, characteristics that are frequently mentioned by VCs as desirable features of start-up teams are industry experience, leadership experience, managerial skills, and engineering/technological skills. However, a consideration of existing findings also shows that current knowledge on VCs' evaluations is still rather general, a critique that has also been voiced by other scholars (Muzyka et al., 1996; Sandberg, Schweiger, & Hofer, 1988; Shepherd & Zacharakis, 1999). First, we still lack knowledge on the importance of different parameter values of particular team characteristics. For instance, relevant parameter values for the characteristic "educational background" might be (1) all team members have management

Table 1

Survey of the Literature

Author(s)	Sample	Method	Evaluation criteria by rank order of importance
Wells (1974)	8 VCs	Personal interviews	(1) Management commitment (2) Product (3) Market
Poindexter (1976)	97 VCs	Mail survey	(1) Quality of management (2) Expected rate of return (3) Expected risk
Johnson (1979)	49 VCs	Mail survey	(1) Management (2) Policy/strategy (3) Financial criteria
Tyebjee and Bruno (1981)	46 VCs	Phone interviews	(1) Management skills and history (2) Market size/growth (3) Rate of return
MacMillan et al. (1985)	102 VCs	Mail survey	(1) Capability for sustained intense effort (2) Familiarity with the target market (3) Expected rate of return
Goslin and Barge (1986)	30 VCs	Mail survey	(1) Management experience (2) Marketing experience (3) Complementary skills in team
Robinson (1987)	53 VCs	Mail survey	(1) Personal motivation (2) Organizational/managerial skills (3) Executive/managerial experience
Rea (1989)	18 VCs	Mail survey	(1) Market (2) Product (3) Team credibility
Dixon (1991)	30 VCs	Personal interviews	(1) Managerial experience in the sector (2) Market sector (3) Marketing skills of management team
Muzyka et al. (1996)	73 VCs	Personal, standardized interviews	(1) Leadership potential of lead entrepreneur (2) Leadership potential of management team (3) Recognized industry expertise in team
Bachher and Guild (1996)	40 VCs	Personal interviews	(1) General characteristics of the entrepreneur(s) (2) Target market (3) Offering (product/service)
Shrader, Steier, McDougall, and Oviatt (1997)	214 new ventures with IPO	Interviews, publicly available documents	(1) Technical education (2) New venture experience (3) Focus strategy
Shepherd (1999)	66 VCs	Conjoint experiment (personal/mail)	(1) Industry-related competence (2) Educational capability (3) Competitive rivalry

education; (2) some have management education/some have engineering education; and (3) all have engineering education. Similarly, relevant parameter values for "industry experience" might be (1) all team members have industry experience; (2) some have industry experience; and (3) none have industry experience. However, the available results do not reveal the relative preference VCs attach to these parameter values. Second, the existing results cannot reveal utility trade-offs between different team characteristics. For example, if a team lacks leadership experience, which potential strengths might compensate for such a shortcoming?

In summary, as knowledge on the *parameter values* of particular team characteristics and on *trade-offs* between different team characteristics is key to understanding VCs' evaluations of start-up teams but still lacking, the first goal of this paper is to provide a focused exploration of team evaluation criteria.

The Role of Experience in VC Decision Making

A recent study by Shepherd et al. (2003) suggests a second important extension to research on VCs' evaluations of venture proposals in general and the evaluation of start-up teams in particular. Drawing on cognitive theory, Shepherd et al. find that the experience of VCs has a significant impact on their decision making. As the evaluation of human capital "has to do with making projections of future behaviors that human capital is likely to perform" (Smart, 1999) and human capital is one of the most important but difficult areas to assess in venture proposals (Kozmetsky, Gill, & Smilor, 1985), novice and experienced VCs may differ in their evaluation of start-up teams.

Cognition research provides valuable insights into the development of expertise in decision making. To arrive at a judgment, decision makers select, combine, and evaluate information cues (Spence & Brucks, 1997). The way in which information cues are processed is influenced by an individual's cognitive structures (schemata). A schema is an organized network of knowledge that includes concepts, facts, skills, and action sequences (Gagné & Glaser, 1987). Schemata thus play an elemental role in all cognitive activities such as predicting, explaining, and developing opinions (Larkin, McDermott, Simon, & Simon, 1980; Matlin, 2005).

Prior research shows that individuals refine their schemata in various ways as they acquire experience in a particular domain. For example, Lurigio and Carroll (1985) suggest that experienced individuals possess more complete and detailed schemata than inexperienced individuals. Experienced individuals also group domain-specific knowledge in more meaningful ways than those with little experience, will draw on clearer concepts, create richer connections between concepts, and will be able to apply domain-specific problem-solving procedures they have developed over time (Adelson, 1981; Gobbo & Chi, 1986; Knowlton, 1997; Matlin, 2005). For instance, they will learn about the importance of different dimensions of a decision problem (Shepherd et al., 2003). With respect to the evaluation of start-up teams, this suggests that VCs will become increasingly knowledgeable about the question of which team characteristics are required for a successful new firm creation.

Research on VCs' decision making has not yet explored whether differences exist between the evaluation of start-up teams by novice VCs and by experienced VCs. However, knowledge on the existence and direction of such experience effects would be key for theory development on VC decision making and also for VC practice and start-up teams. In particular, if it turns out that experience effects play a considerable role in VCs' evaluations, future studies would need to control for that variable.

Against the backdrop of these observations, this paper seeks to contribute to the literature on entrepreneurship by (1) exploring in detail the criteria VCs use in the evaluation of start-up teams and (2) exploring how the decision-making experience of VCs influences the importance attributed to team evaluation criteria.

Method

Our study uses conjoint analysis. As this method allows researchers to *simulate* respondents' decision processes in real time, it is in several ways superior to commonly used *post-hoc* methods that collect data on VCs' self-reported decision policies (Shepherd & Zacharakis, 1999). In a conjoint experiment, respondents are asked to judge a series of profiles, that is, combinations of parameter values for several attributes. From the preferences revealed in this way, conclusions can be drawn about the contribution of the various parameter values of each attribute to the overall valuation a certain profile receives. In particular, trade-offs between different parameter values of the attributes under investigation are quantified. The application of this research method to our study is presented in the following paragraphs.

Focus on the Initial Stage of the Evaluation Process

VCs usually evaluate new venture proposals in a multistage process. An important early stage in this process is the appraisal of the business plan, where the decision is made whether to reject a venture proposal outright or to pursue it further by inviting the management team for a project presentation (Bagley & Dauchy, 1999; Dixon, 1991). Typically, 80% of all business plans submitted to a VC firm are rejected in this first round of evaluations, thus making it an important process for VCs and a crucial hurdle to pass for start-up teams (Roberts, 1991).

Our conjoint analysis focuses on this initial stage in the evaluation process of VCs and uses the team description given in the business plan as the basis for a decision experiment. Three arguments support the choice of this approach.

First, when studying team evaluation criteria it is important to define the stage in the decision process where these criteria are applied.[1] For example, whereas a team's educational background can be observed in the written business plan, the atmosphere within the team can only be observed during personal presentations, and qualities such as perseverance and stress resistance will only be observable in the long run.

Second, selecting the initial stage of the evaluation process is advantageous as the team characteristics given in a business plan are comparatively objective, unlike criteria such as personal fit within the team, which VCs can only observe in later stages. Hence, the characteristics of the hypothetical teams in our study could be communicated unambiguously to the participants.

Third, the evaluation of the start-up team's description in a business plan is well suited for a conjoint approach. Unlike in most other conjoint experiments, where the respondent has to imagine some real-world object based on a description on the conjoint card, the team description provided on our conjoint cards is of the same nature as the object itself (the team description given in the business plan). Thus, despite some necessary simplifications in team descriptions, the conjoint design employed here is relatively realistic, as the conjoint task closely resembles the task performed by the respondent in real life.

Construction of Team Descriptions

An important issue in conjoint analyses is to keep the thought-experiments manageable for the interviewees. As the literature review has shown, prior studies suggest

1. Although criteria related to the start-up team are consistently ranked among the most important criteria in VCs' decision making, there is also some scholarly debate on whether team criteria are of similar importance throughout the different stages of the evaluation process. To date, only a few studies have differentiated between various evaluation stages. For example, the findings of Hall and Hofer (1993) suggest that human capital characteristics do not play a major role during the screening stage of venture proposals; however, their study also indicates that VCs do evaluate team characteristics during this stage. More recent ethnographic findings by Silva (2004) suggest that the description of human capital is an important source of information in the screening stage.

Table 2

Percentage of Teams with a Given Parameter Value That Are Ranked in the Top Quintile

Variable	Parameter value 1	Parameter value 2	Parameter value 3
Relevant industry experience	0.8% none	25.5% some	35.9% all
Field of education	12.4% all management	38.9% some management, some engineering	11.5% all engineering
Experience in leading teams (5–10 people)	6.5% none	24.9% some	26.6% all
Acquaintance among team members	17.1% brief	16.8% for a longer time, privately	27.1% for a longer time, professionally
Level of education: university degree	7.5% none of the team members	27.2% some team members	23.5% all team members
Age of team members	12.4% 25–35 years	33.7% 35–45 years	15.4% 25–45 years
Prior job experience: type of firm	15.0% mostly large firms	24.5% some large firms, some start-up	22.2% mostly start-up

that VCs regard industry experience, leadership experience, managerial skills, and engineering/technological skills as key characteristics of start-up teams. Yet it would be problematic to include only these potentially important characteristics in a thought-experiment. Thus, to identify any additional team characteristics frequently used in team descriptions and thus subjected to VCs' evaluations, we conducted a pilot study that comprised seven exploratory interviews with VCs and a thorough analysis of two dozen real business plans. This led us to include four additional team characteristics—level of education, type of job experience (start-up vs. large firm), age, and mutual acquaintance within the team—to the criteria already mentioned earlier. Moreover, the pilot study provided information on the relevant parameter values for each of the seven team characteristics. For each characteristic, we included three different parameter values (Table 2).

The team size was fixed at four members. This was done for several reasons: First, our analysis of team descriptions in business plans showed that this is a common size for start-up teams. Second, as VCs usually provide support in finding individuals who could fill an open position in a management team, introducing varying team sizes into our conjoint design did not seem particularly important. Having an even number of team members also has the advantage that team attributes described as "some management, some engineering education" could be interpreted as an even split between the two subgroups. From these attributes and parameter values, we generated 20 profiles (a reduced set with two holdouts) using a full rank order method of conjoint analysis. These cards were pretested with five VCs, who confirmed that the team attributes and their parameter values given on the conjoint cards were adequately chosen and that the task of ranking 20 hypothetical team profiles was indeed manageable.

Figure 1

Description of the Venture as Presented to Interviewees

- Project is based on a *patented technical product*
- Considerable *cost savings* for users
- *Value proposition* is clearly visible
- Potential users are *small and medium-sized industrial firms*
- A working *prototype* exists

Venture Type

In conducting our conjoint experiment, we accounted for the fact that the evaluation of the start-up team is dependent on the type of venture project. For example, while new ventures in biotechnology usually need qualified scientists, new ventures in the software industry rely on founders who possess IT knowledge. As a result, it was necessary to specify the type of new venture that the start-up team under consideration wanted to pursue. On the other hand, an overly detailed description of the venture would have considerably raised the probability that individual respondents would identify the hypothetical start-up with a particular real investment experience, thus jeopardizing the generality of our analysis. So, after discussing several alternative descriptions with experts from the VC industry, we decided to employ a description that indicates several characteristics of the hypothetical venture but at the same time remains sufficiently general (see Figure 1).

Sample

Our sample consists of 51 conjoint experiments/interviews[2] that were conducted at 26 different VC firms located in Munich, Berlin, and Vienna. All of the respondents were actively involved in the evaluation of business plans. Apart from the conjoint experiments, background information on the respondents (age, education, professional experience, experience as a VC) and on the VC firms (size, volume of funds, specialization in industries or financing stages, evaluation process) was collected. As we used a convenience sample, our sample of VC firms cannot claim to be representative. A truly random sample of interviewees is difficult to obtain given the time constraints in the VC industry and the time required for interviews (Smart, 1999). However, we did make efforts to obtain a mix of different types of VC firms. The description in Table 3 shows that our sample contains VC firms of different sizes, different industry focus, and different degrees of internationalization. Since the VC firms were chosen to match our hypothetical venture project, obviously more of them invest in telecommunications, software, and e-commerce than in biotechnology. With regard to experience, our sample covers a sufficiently broad range in order to investigate the impact of different levels of experience. While the average

2. As Shepherd and Zacharakis (1999) suggest as a rule of thumb, a sample size greater than 50 is normally sufficient. Previous studies used sample sizes of 73 VCs (Muzyka et al., 1996), 53 VCs (Zacharakis & Meyer, 1998), and 66 VCs (Shepherd, Ettenson, & Crouch, 2000).

Table 3

Demographics of VC Firms and Individuals Surveyed

VC firms (N = 26)		
Firm age (years):	mean = 8.2, standard deviation (SD) = 12.6, median = 3, range: 1–56	
Firm size (number of professionals):	mean = 75.4, SD = 202.8, median = 9, range: 1–800	
Volume of funds (EUR):*	<10 m: 2; 26–100 m: 8; 101–250 m: 5; >250 m: 9; n.a.: 2	
Investment stage:*,**	seed: 10; start-up: 17; first stage: 20; expansion: 17; later stages: 8	
Industry focus:*,**	telecommunication: 23; software: 22; e-commerce: 19; electrical engineering: 13; biotechnology: 10; services: 5; other: 13	
Location of interviews (offices):*	Munich: 40; Vienna: 7; Berlin: 4	
Individuals (N = 51)		
Age:	mean = 35.0, SD = 6.7, median = 34, range: 24–57	
Education level:*,**	apprenticeship: 4; university degree: 51; MBA: 15; doctorate: 11	
Education type:*,**	business/economics: 39; engineering: 18; science: 6; law: 3; other: 2	
VC experience (years):	mean = 3.9, SD = 5.2, median = 2, range: 0–30	
Tenure with firm (years):	mean = 2.4, SD = 2.0, median = 2, range: 0–11	
Number of business plans evaluated:	mean = 460, SD = 455, median = 300, range: 0–2000	
Prior professional experience:	Type of firm:*,**	start-up: 22; SME: 23; large firm: 35; no prior experience: 0
	Industry:*,**	management consulting: 28; manufacturing: 25; financial services: 13; other: 9
Leadership experience:*	none: 9; 1–5 subordinates: 20; 6–20 subordinates: 16; >20 subordinates: 6	

* For categorical variables, the number of respondents who chose the respective category is given; ** Multiple answers possible.

experience is almost 4 years of work as a VC, a substantial number of VCs interviewed had experience of 2 years or less (which is typical of the relatively young German VC industry).[3]

The conjoint experiments were conducted according to a fixed scheme by one interviewer who was present during the entire experiment. None of the participants encountered any problems in ranking the conjoint cards.

Analysis

We employ discrete choice methodology to identify the impact of various team characteristics on VCs' evaluations. Our model interprets the 20 rankings assigned to the simulated teams by each of our respondents as a rank ordering of choices from a given set. A suitable estimator to analyze such data has been proposed by Beggs, Cardell, and Hausman (1981). Following Marden (1995), the model is also known as the Plackett-Luce or as the "exploded logit" model. The marketing literature refers to the model as the choice-based conjoint analysis method.

3. Measuring experience by the number of years a decision maker has worked as a VC was suggested by Shepherd et al. (2003). We also used the alternative operationalization of experience as the logarithm of the number of years the rater had been working as a VC. While the explanatory variables that are significant in this specification are also significant in the basic one—hence, the results do not contradict each other—some other coefficients lose their significance in the log specification. The likely explanation of this finding is that the logarithmic function is too steep for small values of the argument and too flat around the median. We therefore chose the dummy operationalization as the most appropriate one.

To consider an example, an individual's ranking of A-C-B-D in a choice set (A, B, C, D) is taken to represent an observation in which A is chosen as the most preferred alternative from the full set (A, B, C, D); C is the preferred alternative from the restricted set (B, C, D); and B is chosen as the preferred alternative from the set (B, D).[4] The model thus extends McFadden's conditional logit to cases in which full ranking data are available.

Our model presumes that all alternatives are assessed by our subjects using a cardinal assessment function that reflects the quality of the team (and thus the likelihood of obtaining a favorable financing decision) as a linear additive function of team characteristics. Let the venture capitalist's assessment be denoted b_{ik} for the benefit that venture capitalist i would be able to draw from financing team k (out of a set of K alternatives). The ranking chosen by each venture capitalist emerges from a simple ordering of the K alternatives according to their b_{ik} values, which are functions of the team characteristics $b_{ik} = X_{ik}\beta + \varepsilon_{ik}$, where X_{ik} is a row vector of the characteristics of alternative k and (possibly) interaction terms between the characteristics of alternative k and of rater i, and β is a column vector of coefficients. Under the assumption that the error term ε_{ik} follows an independent identically distributed extreme value distribution, the probability that any alternative k is ranked as the best one by respondent i is given by

$$\text{(1)} \qquad \text{prob}\left\{b_{ik} > \max\left(b_{ij}\right)_{j \neq k}\right\} = \exp(X_{ik}\beta) \big/ \left(\Sigma_j \exp\left(X_{ij}\beta\right)\right).$$

Returning to our earlier case in which the sequence of A-C-B-D is chosen from the choice set (A, B, C, D), the probability of observing this ranking from rater i would be given by[5]

$$\begin{aligned} \text{(2)} \qquad \text{prob}\{\textit{ranking A-C-B-D}\} = {} & \left[\exp(X_{iA}\beta) \big/ \left(\Sigma_{j=A,B,C,D} \exp\left(X_{ij}\beta\right)\right)\right]. \\ & \left[\exp(X_{iC}\beta) \big/ \left(\Sigma_{j=B,C,D} \exp\left(X_{ij}\beta\right)\right)\right]. \\ & \left[\exp(X_{iB}\beta) \big/ \left(\Sigma_{j=B,D} \exp\left(X_{ij}\beta\right)\right)\right] \end{aligned}$$

In order to ensure convenient interpretation of our coefficient signs, we use the following parameter values as reference groups: age of team members between 25 and 35 years; no team member with a university degree; all team members have management education; team members have mostly large-firm experience; no team member with experience in the relevant industry; no team member with experience in leading teams of 5–10 individuals; and team members have known each other for a short period of time. This choice of reference parameter values is based on the descriptive data analysis (see Table 2, next section) and is made in such a way that the reference parameter value is presumably the one with the lowest benefit.

In our estimation, a team with these parameter values will automatically be assigned a benefit value of zero since the associated coefficient vector β is implicitly set to zero. In order to model parameter values deviating from the reference team, we employ a dummy variable technique where a separate dummy is used for the two other parameter values of each team variable. In addition, we interact, in the extended specification, all terms with a dummy variable Δ_i indicating that rater i's experience is above the median. Hence, our full specification of the benefit b_{ik} that rater i would expect to derive from team k can be written as follows:

4. We use the model implementation in STATA 8.0 (command rologit).

5. A more detailed derivation of the likelihood function for this model is given in Hausman and Ruud (1987, p. 86).

$$b_{ik} = \sum_{j=1}^{7} \left(\beta_{j1} D_{j1k} + \beta_{j2} D_{j2k} + \beta_{j3} \Delta_i D_{j1k} + \beta_{j4} \Delta_i D_{j2k} \right) + \varepsilon_{ik}$$

Empirical Results

Descriptive Analysis

Before turning to multivariate analysis, we briefly explore some simple associations between the ranking of the team, that is, the level of team success, and the variables that presumably have an impact on success in order to give some intuition on the findings and demonstrate their robustness. We measure the success of each team by computing the share of cases in which the team was ranked among the top four teams, the upper quintile. This share variable can be interpreted as the team's likelihood of reaching a certain cutoff level (the top 20%), which would (hypothetically) lead to an invitation to meet with a VC.[6]

Table 4 lists the teams and their characteristics in the order of the share of top quintile rankings achieved in our conjoint design. Since we use a reduced conjoint design, the "dream team" configuration, that is, the theoretically best profile, will not necessarily be among the 20 profiles presented to the interviewees. Team 10, which receives top quintile rankings in 96.1% of all cases, is therefore the most preferred team in the choice set according to our success variable, but not necessarily the theoretically optimal team configuration. While Table 4 shows that the top quintile share decreases quickly among the first 10 teams, it is difficult to extract clear information on the relative contribution of the various team characteristics from the simple ranking performed here. However, there appears to be a positive relationship between (favorable) ranking and industry experience, leadership experience, and the age of team members. It is more difficult to derive clear statements with respect to the other variables from the aggregate ranking information.

Whereas Table 4 shows complete team profiles, Table 2 presents the "success information" treating the parameter values of the team characteristics as fully independent. This table allows us to get a clearer impression of which team characteristics and which parameter values are likely to be important. For example, in 6 of our 20 team descriptions all team members have industry experience. Given 51 interviews, this yields 306 observations, of which 110 (35.9%) were ranked among the top four teams.

For the attributes "industry experience," "field of education," "acquaintance," and "age," we find a clear preference for a particular parameter value in that the distance from the respective next-best parameter value is larger than 10%. Preferred teams are those in which all members have industry experience, their educational background is mixed (some engineering, some management expertise), founders have known each other for a longer time professionally, and members are older (aged 35–45).

For the remaining three characteristics, a somewhat less transparent picture emerges: With regard to university training, prior job experience in corporate or start-up environments, and leadership experience, the best and second-best parameter values do not differ greatly when evaluated according to the share of top quintile rankings.

6. Obviously, taking the top quintile as our measure is an arbitrary choice. However, it does represent a reasonable compromise, as taking the share of top rankings (i.e., how often a team is considered the best one) would lead to an ambiguous result for many teams that never reach that position, while taking the top ten ranking would not discern very clearly between "above-average" teams of similar quality.

Table 4

Descriptive Statistics on Team Characteristics

Team number	Share of top quintile rankings (%)	Relevant industry experience	Field of education	Leadership experience	Acquaintance among team members	University degree	Age of team members	Prior job experience
10	96.1	All	Mixed	Some	Professional	Some	35–45	Start-up
3	60.8	Some	Mixed	All	Brief	Some	25–45	Mixed
13	58.8	Some	Mixed	All	Private	All	35–45	Corporate
16	47.1	All	All engineering	Some	Brief	All	35–45	Mixed
15	25.5	All	All management	All	Private	All	25–35	Start-up
8	25.5	All	All management	All	Professional	None	25–45	Mixed
6	23.5	Some	All management	Some	Professional	Some	25–35	Corporate
19	15.7	Some	All engineering	All	Private	All	25–45	Corporate
5	11.8	Some	All engineering	None	Professional	All	25–45	Start-up
7	11.8	All	Mixed	None	Brief	None	25–35	Corporate
12	9.8	All	All engineering	None	Private	Some	25–45	Corporate
2	7.8	Some	All engineering	Some	Private	None	25–35	Mixed
18	5.9	None	Mixed	None	Professional	All	25–35	Mixed
14	0.0	None	All engineering	All	Professional	None	35–45	Corporate
9	0.0	None	Mixed	Some	Private	None	25–45	Start-up
11	0.0	Some	All management	None	Brief	None	35–45	Start-up
4	0.0	None	All engineering	All	Brief	Some	25–35	Start-up
1	0.0	None	All management	Some	Brief	All	25–45	Corporate
20	0.0	None	All engineering	Some	Brief	Some	25–45	Corporate
17	0.0	None	All management	None	Private	Some	35 to 45	Mixed

Note that Table 2 summarizes seven bivariate relationships—it is therefore not a substitute for a multivariate analysis. Nor does this table give us the opportunity to generate inference results. Hence, while Tables 2 and 4 provide some indication of which team characteristics are particularly important, a multivariate treatment of the data is required in order to arrive at a more structured response to our research questions.

Discrete Choice Analysis—Model Specification

The results of estimating the rank-ordered logit model are presented in Table 5. In specification (1), we use only the team characteristics as explanatory variables, while in specifications (2) to (5) we introduce interaction terms with the dummy variable Δ_i, which indicates whether the rater is an experienced VC. In essence, the upper half of columns (2) to (5) (i.e., those coefficients shown in the first part of Table 5) describe the choice behavior of less experienced VCs, while the lower half describes the difference between the preferences of more and less experienced raters.

Before interpreting the results, we need to discuss whether our findings are consistent with the assumption that our subjects have provided us with full rankings of the alternatives. There is considerable doubt in the literature that this assumption is always justified (Hausman & Ruud, 1987). What might have happened—and comments from our interviewees provide some evidence to this effect—is that subjects do spend effort on the upper ranks but pay less attention to the lower ones. In this case, heteroscedasticity will be introduced, which (in this model) will lead to inconsistent estimates if the full ranking information is used. For this reason, we present several specifications that differ with respect to the number of ranks taken into account. In columns (1) and (2) of Table 5, we present rank-ordered logit estimates which take the full rankings at face value. In specifications (3)/(4)/(5), in contrast, only the top 16/12/8 ranks are taken into account, while the residual ranks are treated as noninformative.

In essence, we discard information in columns (3) through (5) and should thus expect the precision of our estimates to decrease as more and more rankings are discarded. Indeed, even a cursory glance at the results shows that standard errors increase monotonically from column (2) to column (5). Moreover, the estimates show a second well-known pattern—the coefficients increase in size as we discard more of the lower ranks in our estimate. Hausman and Ruud (1987) argue that this phenomenon is consistent with the lower ranks being evaluated less carefully than the upper ones.[7] Still, while the coefficients increase overall, their relative size remains largely stable.

Discrete Choice Analysis—Pooled Results

We start by discussing the pooled results for all respondents (specification [1]) before addressing the differences due to the rater's level of experience. In discussing the pooled results, we first analyze the relative importance of the various team characteristics and then address the benefit contribution of the various parameter values for each characteristic. Finally, we consider trade-offs between different parameter values for different characteristics.

7. We did, in fact, estimate models for all possible specifications, both with and without interaction terms: using all ranks, the top 19 ranks, etc. down to using only the top 6 ranks (with even fewer ranks, convergence was not attained). With very few exceptions, the coefficients' signs and significance levels remain stable.

Table 5

Rank-Ordered Logit Results

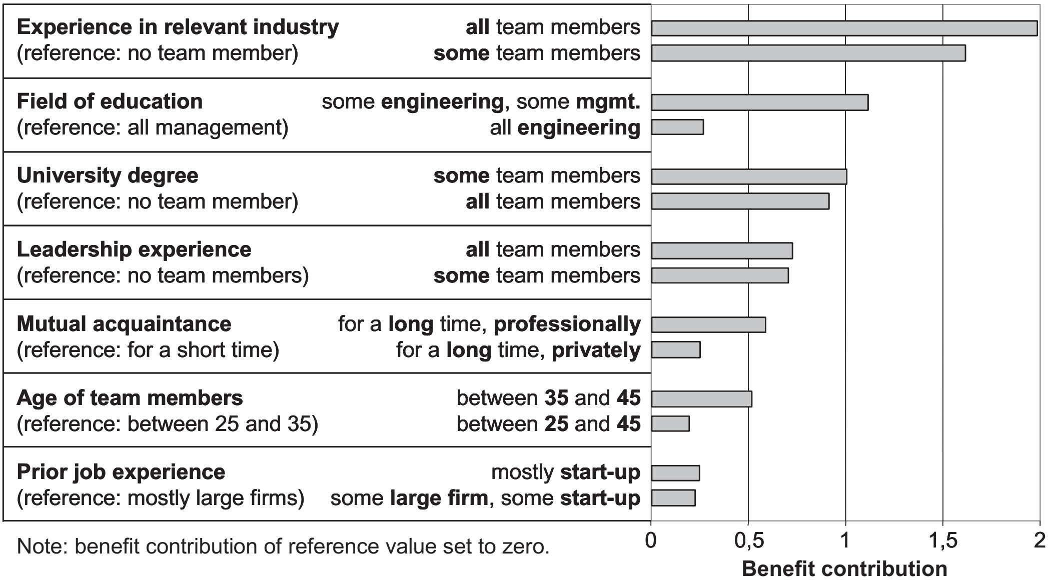
Explanatory variables: Team characteristics. In spec. (2) to (5), coefficients refer only to inexperienced VCs	(1) No interactions, all 20 ranks	(2) With interactions, all 20 ranks	(3) With interactions, top 16 ranks	(4) With interactions, top 12 ranks	(5) With interactions, top 8 ranks
Experience in relevant industry—all team members	1.986***	1.980***	1.992***	2.278***	2.767***
	(0.191)	(0.241)	(0.254)	(0.253)	(0.371)
Experience in relevant industry—some team members	1.614***	1.519***	1.476***	1.649***	1.706***
	(0.165)	(0.205)	(0.218)	(0.240)	(0.281)
Field of education—all engineering	0.265**	0.462**	0.488**	0.653**	0.860**
	(0.120)	(0.201)	(0.201)	(0.288)	(0.354)
Field of education—some engineering, some mgmt.	1.113***	1.194***	1.269***	1.497***	2.031***
	(0.127)	(0.198)	(0.213)	(0.271)	(0.346)
Leadership experience—all team members	0.725***	1.001***	1.029***	1.165***	1.498***
	(0.116)	(0.173)	(0.195)	(0.264)	(0.341)
Leadership experience—some team members	0.704***	1.012***	1.078***	1.129***	1.650***
	(0.111)	(0.161)	(0.175)	(0.213)	(0.320)
Acquaintance—for a long time, professionally	0.585***	0.300*	0.321**	0.408**	0.831***
	(0.143)	(0.153)	(0.147)	(0.187)	(0.240)
Acquaintance—for a long time, privately	0.247**	–0.034	–0.033	–0.048	0.082
	(0.121)	(0.134)	(0.109)	(0.148)	(0.236)
University degree—all team members	0.912***	1.505***	1.577***	1.432***	2.144***
	(0.149)	(0.236)	(0.270)	(0.296)	(0.353)
University degree—some team members	1.003***	1.332***	1.363***	1.213***	1.530***
	(0.110)	(0.169)	(0.214)	(0.192)	(0.208)
Age of team members between 25 and 45	0.191***	0.128	0.096	–0.011	0.148
	(0.070)	(0.079)	(0.080)	(0.100)	(0.201)
Age of team members between 35 and 45	0.517***	0.517***	0.397***	0.237	–0.270
	(0.101)	(0.166)	(0.153)	(0.156)	(0.265)
Prior job experience—some large firm, some start-up	0.221**	0.176*	0.181	0.084	0.053
	(0.087)	(0.106)	(0.111)	(0.108)	(0.157)
Prior job experience—mostly start-up	0.246***	0.273**	0.204	0.217	–0.090
	(0.083)	(0.117)	(0.134)	(0.140)	(0.126)

Explanatory variables: team characteristics interacted with dummy variable Δ_i ($\Delta_i = 1$ if rater is experienced)					
$\Delta_i \times$ experience in relevant industry—all team members		0.258	0.345	0.392	0.223
		(0.391)	(0.420)	(0.400)	(0.478)
$\Delta_i \times$ experience in relevant industry—some team members		0.326	0.436	0.470	0.624
		(0.356)	(0.381)	(0.382)	(0.411)
$\Delta_i \times$ field of education—all engineering		−0.397	−0.330	−0.289	−0.103
		(0.251)	(0.292)	(0.426)	(0.539)
$\Delta_i \times$ field of education—some engineering, some mgmt		−0.170	−0.098	−0.050	−0.084
		(0.257)	(0.284)	(0.375)	(0.498)
$\Delta_i \times$ leadership experience—all team members		−0.487**	−0.456*	−0.531*	−0.538
		(0.224)	(0.239)	(0.299)	(0.447)
$\Delta_i \times$ leadership experience—some team members		−0.558***	−0.607***	−0.668**	−0.885**
		(0.200)	(0.211)	(0.264)	(0.430)
$\Delta_i \times$ acquaintance—for a long time, professionally		0.635**	0.811**	1.035**	0.769
		(0.308)	(0.327)	(0.417)	(0.474)
$\Delta_i \times$ acquaintance—for a long time, privately		0.587**	0.676**	0.983***	0.582*
		(0.265)	(0.278)	(0.326)	(0.347)
$\Delta_i \times$ university degree—all team members		−1.127***	−1.262***	−1.249***	−1.903***
		(0.275)	(0.309)	(0.353)	(0.445)
$\Delta_i \times$ university degree—some team members		−0.644***	−0.799***	−0.667***	−0.864***
		(0.213)	(0.241)	(0.244)	(0.308)
$\Delta_i \times$ age of team members between 25 and 45		0.187	0.172	0.206	−0.167
		(0.148)	(0.160)	(0.197)	(0.320)
$\Delta_i \times$ age of team members between 35 and 45		0.071	0.210	0.439**	0.591
		(0.206)	(0.199)	(0.212)	(0.396)
$\Delta_i \times$ prior job experience—some large firm, some start-up		0.216	0.232	0.451**	0.472*
		(0.165)	(0.175)	(0.209)	(0.246)
$\Delta_i \times$ prior job experience—mostly start-up		−0.037	0.077	0.092	0.275
		0.258	0.345	0.392	0.223
Observations	1,020	1,020	1,020	1,020	1,020
Log L	−1,834.9	−1,796.3	−1,632.3	−1,267.2	−836.2
Pseudo R^2	0.150	0.168	0.183	0.217	0.266
Chi-squared	447.1	951.5	934.6	746.4	837.19
Df	14	28	28	28	28

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 2

Benefit Contributions of Parameter Values of Team Characteristics (Specification [1])



We define the "importance" of a characteristic as the difference between the benefit contributions (i.e., the estimated coefficient) of the most and least preferred parameter values, normalized such that the sum of all importance values yields 100%. In other words, the importance of a characteristic is that share of the value difference between the best and the worst possible team that can be attributed to this characteristic.[8] Given that the reference parameter value, by construction, has a benefit contribution of zero for most characteristics, the importance is essentially the (normalized) benefit contribution of the most preferred parameter value.[9]

As Figure 2 illustrates, industry experience is by far the most important characteristic (32.2%). While this in itself is not a new insight, our approach allows a meaningful comparison of characteristics beyond a mere ordering of their relative importance. In

8. The importance of a characteristic obviously depends on the available parameter values. The more similar these are, the lower the characteristic's importance will turn out to be. Hence, "importance" must be interpreted with the underlying parameter values in mind. For this reason, a realistic choice of parameter values for our experiment was paramount. Note that by explicitly defining the parameter values we avoid another problem of surveys using rating scales: When asked about the importance of industry experience, for example, each respondent bases his or her assessment on personal experiences regarding this characteristic's typical parameter values. A VC who has never seen a team without industry experience will likely attribute lower importance to this characteristic than one who has.

9. In more detail, the importance values are calculated as follows. The contribution of industry experience to the overall score of the best team, compared to that of the worst team, equals 1.986 (see Figure 2 or the first column of Table 5), that of the field of education 1.113, that of leadership experience 0.725, etc. Normalization then yields the numbers given in the text following this footnote: 1.986/(1.986 + 1.113 + 0.725 + . . .) = 0.322, etc.

particular, we find that industry experience is 1.8 times—i.e., almost twice—as important as the field of education, which ranks second in overall importance (18.0%). Third comes academic education with 16.2%, meaning that it is about half as important as industry experience. Less importance is attributed to leadership experience (11.7%), the team members' mutual acquaintance within the team (9.5%), and age (8.4%). The type of prior job experience ranks last at 4.0%.

We now delve deeper into the benefit contributions of each characteristic's parameter values. To begin with, we find that the marginal benefit contribution of having more team members with *industry experience* decreases strongly. When only some team members have relevant experience, the benefit contribution (1.61) is about 80% of that attained when all founders know the industry (1.99). Hence, while having no industry experience seems to be a *conditio sine qua non* (knock-out criterion) for a VC evaluating a venture team, it will often be sufficient to have some industry insiders on board.

For the *field of education*, the relative benefit contribution of the various parameter values confirms the insight that a heterogeneous team comprising technical and management skills is much desired (benefit contribution 1.11). A management-only team is clearly not *viable* (benefit contribution 0), which was to be expected given the technical nature of our business model. Despite the model's technical nature, however, teams consisting entirely of engineers also fare so badly that this parameter value (benefit contribution 0.27) seems like a disqualifier for advancing to further stages in the evaluation process.

For the team's *level of education*, we find that an academic background is essential, but that it hardly makes a difference whether some or all team members have an academic background. While a team with only some university graduates is slightly preferred, the difference between the two coefficients in Table 5 is insignificant. This could mean that VCs see the participation of founders with university degrees as a positive signal—which, however, does not improve further when the number of graduates in the team increases from "some" to "all"; in fact, it decreases. Alternatively, an "all university" team may mean a higher average level of human capital, while a mixed team offers (desirable) heterogeneity. When these two effects are of equal size, we should observe (as we do) equal benefit contributions for both parameter values.

For *leadership experience*, we find a pattern similar to the one identified for industry experience. Having no members with leadership experience (benefit contribution 0) is likely to be a knock-out criterion in the evaluation process. However, the benefit contribution of "some team members with leadership experience" (0.70) is nearly identical to that of "all team members" (0.73). This is a rather plausible finding since not all members in a venture team can assume a leadership role. Note, however, that this is only true in the early stages of the start-up, whereas after successful expansion all founders might find themselves in leading positions and thus need leadership experience.

With regard to *mutual acquaintance*, we find that the type of acquaintance is just as important as its duration. Being acquainted for a long time is less than half as valuable (benefit contribution 0.25) when based on private relationships than when it is based on professional collaboration (benefit contribution 0.59).

As for *age*, we find that having only young team members (aged 25–35) on board yields the lowest evaluation (zero). This result is consistent with anecdotal evidence from VCs who had negative experiences with "boy groups" during the e-commerce boom. What is surprising is that having some more senior people in addition to young members on the team only partly remedies the problem: A mixed team with members aged between 25 and 45 (benefit contribution 0.19) still fares much worse than a team consisting exclusively of older founders (35–45, benefit contribution 0.52).

Finally, for the *type of prior job experience*, we find similar positive benefit contributions for heterogeneous teams (i.e., those whose members have experience partly in large firms, partly in start-ups) (0.22) and teams in which members have only start-up experience (0.25). However, even though both coefficients are significant, their size shows that VCs seem to care comparatively little about this team characteristic.

Discrete Choice Analysis—Effects of VC Experience

We now explore whether VC experience has a significant moderating effect on the evaluation of start-up teams. Overall, we find that both more and less experienced raters attach the highest importance to industry experience and the lowest to the type of prior professional experience. However, our analysis also reveals some key differences. The level of academic education ranks second for less experienced VCs (importance: 22.1%) and only fourth for their more experienced colleagues (10.8%). Leadership experience is ranked fourth (14.8%) by novices and sixth (8.1%) by experienced raters. The latter, in turn, attach more importance to mutual acquaintance within the team (ranked third at 14.7%) than less experienced VCs (ranked sixth at 4.9%).

Table 5 provides more detailed insights into the ratings of novice and experienced VCs. As specifications (2) to (5) show, we consistently find significant differences between the preferences of novice and experienced VCs for each parameter value of the following three characteristics: leadership experience, mutual acquaintance, and academic education. In addition, heterogeneous prior job experience (some start-up, some large firm) receives significantly higher ratings from experienced raters in specifications (4) and (5), as does a higher age (35–45) in specification (4). As the results of specifications (2) to (5) are identical in qualitative terms, and as we seek comparability with the basic model (1), the following discussion will focus on specification (2).

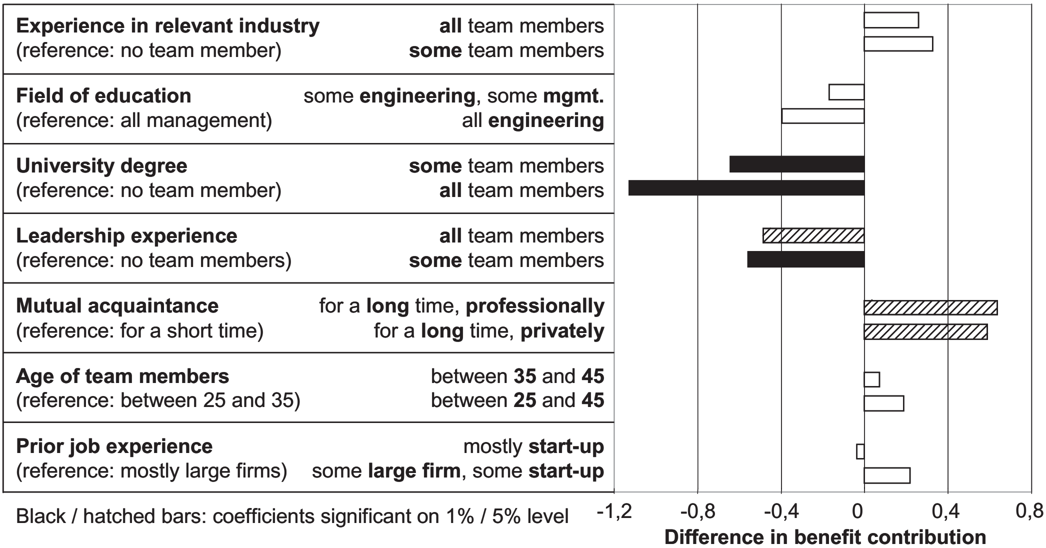
Figure 3 displays the coefficients of the interaction terms as given in the second part of Table 5. Coefficients significantly different from zero on the 1% level are rendered as solid black bars, those significant on the 5% level as hatched bars. We find the largest and most significant differences between novice and experienced raters in the perceived benefit contribution of a university degree. All team members having a university degree leads to a benefit contribution of 1.51 for a novice VC and of only 0.38 (i.e., 1.51–1.13) for experienced VCs. While the latter value is still positive and significantly different from zero (1% level), it is only a quarter of the size of the value for novices. We obtain similar results for the benefit contribution of "*some* team members having a university degree": 0.69 for more vs. 1.33 (1% level) for less experienced VCs, a difference of −0.64 (see Figure 3). Furthermore, the preference order between purely academic and mixed teams is reversed for experienced raters: With a difference of 0.21, they significantly (1% level) prefer mixed teams, while their less experienced colleagues (insignificantly) prefer, by a margin of 0.17, teams in which all members have a university degree.

Leadership experience is also valued significantly less by experienced raters. Novices value leadership experience with a benefit contribution of 1.0 and attach little importance to whether all or some team members have such experience. In both cases, the benefit contributions perceived by experienced VCs are smaller by a value of roughly 0.5. While they are still highly significant (1% level), they are only about half as large as the values we obtained from less experienced raters.

The one characteristic for which we find a significantly *higher* valuation among experienced raters is mutual acquaintance within the team. If team members have known each other for a long time professionally, senior VCs perceive a benefit contribution that is 0.64 higher than their younger colleagues (0.94 vs. 0.30). Given a long-standing *private*

Figure 3

Difference in Benefit Contributions between Experienced and Novice Raters (Specification [2]). Reading Example: Experienced VCs Rate "Mutual Acquaintance for a Long Time, Professionally" 0.64 Points Higher



acquaintance, the difference is 0.59, with novices perceiving no benefit contribution at all (–0.03, not significant) in that parameter value.

Discussion

Criteria related to the start-up team are key in VCs' evaluation of venture proposals. We believe that this study makes two contributions to the literature. First, by focusing on VCs' evaluations of venture teams, we offer more detailed insights on desired team characteristics than previous research. Second, our study extends the research of Shepherd et al. (2003) comparing decision making by VCs with varying experience. Our analysis reveals significant differences between novice and experienced VCs' evaluations. We discuss these two contributions and their implications for research and practice in turn.

Team Characteristics and Trade-Offs

Our findings indicate that industry experience, educational background, and leadership experience are the three most important team characteristics. These general results are consistent with the findings of most prior studies (see "Review of Prior Research" and Table 1).

Our results go beyond the existing research by indicating the importance of different parameter values and by providing insights on utility trade-offs between different team characteristics. For industry experience as well as leadership experience, we find that it may suffice when only some team members possess it. Regarding the field of education, heterogeneous teams are strongly preferred over teams where all members have an engineering background or a management background.

As illustrative examples, consider the following *ceteris paribus* comparisons. A team whose members have known each other privately for a long time and are between 35 and 45 years old receives the same evaluation as a team whose members have a long-standing professional acquaintance and who are (all or some) between 25 and 35 years of age. That is, the bonus of a more senior team equals that of being acquainted for a long time through a professional (not a private) relationship. As a second example, consider team A, in which all members have industry experience, compared to team B, in which nobody knows the industry. We know from anecdotal evidence as well as our analysis that team B has hardly any chance of being considered for funding. However, despite its high level of industry experience, even team A is not guaranteed success if it performs badly in too many other dimensions. Hence the question: What other shortcomings have, in sum, the same effect as a lack of industry experience? According to our results, the two teams will receive roughly the same evaluation if the members of team B have a mixed educational background (some management, some engineering), some or all have a university degree, and they have known each other for a long time privately, while team A consists entirely of engineers with no university degree and only a short mutual acquaintance. In other words, the latter three parameter values lead to a penalty corresponding to that of having no industry experience—and will likely mean no funding for these founders.

Evaluations by Novice vs. Experienced VCs

Our results also go beyond existing research by exploring whether VCs' experience has a significant moderating effect on the evaluation of start-up teams. On the one hand, we find that novice and experienced VCs both see *industry experience* as the most important criterion. Both groups also rank the *field of education* among the top three criteria, and the type of prior professional experience as the least important criterion. On the other hand, however, novice and experienced VCs also critically diverge in some of their preferences. The most striking difference is *mutual acquaintance* among team members, which is ranked among the *top three* criteria by experienced *VCs*, whereas novice VCs rank it in the *second to last* spot.

In order to illustrate the size of the experience effect, consider a team in which no founder holds a university degree and whose members have known each other professionally for a long time. *Ceteris paribus*, this team's evaluation by an experienced VC would be 1.76 points higher than that of a novice—a utility difference nearly as large as the one between all team members vs. no team members having industry experience (1.99).

We view the rankings of experienced VCs to be more valid indicators of desirable team characteristics, although the beneficial effect of growing expertise has not remained unchallenged. The aforementioned empirical study by Shepherd et al. (2003) provides evidence of a curvilinear relationship between VC experience and decision performance, and suggests that decision effectiveness declines after approximately 14 years of experience in venture capital. Yet as most VCs in our "experienced" group are well below this 14-year threshold, we believe that their evaluations are indeed more valid indicators of desirable team characteristics than those made by novice VCs.

Apart from the important finding that novice and experienced VCs differ significantly in certain preferences, an interesting pattern emerges with respect to the type of criteria valued differently by both groups. Our results suggest that team cohesion (as evidenced by mutual acquaintance among team members) is of high importance to experienced VCs, whereas novice VCs tend to emphasize individual-level, more tangible characteristics such as university degrees and prior leadership experience in start-up teams. Using a somewhat clichéd yet still useful metaphor, it seems that experienced VCs attribute relatively more importance to the "forest" than to the "trees" when evaluating start-up teams. More research is needed to see whether this pattern holds in the evaluation of full venture proposals.

Implications for Start-Up Teams and VCs

For start-up teams seeking VC backing or consultants advising teams in early-stage venture development, our results offer an opportunity for team assessment. Provided with a more detailed understanding of the criteria VCs apply in their decision making, incomplete teams can try to find additional members to optimize their profile and their chances of obtaining VC financing. Faced with a choice between multiple potential new members, our results offer guidance as to who will make the best complement for a team. When a new firm has a high-quality team in place, our results will help team members make a clear and concise presentation of the team's quality in the business plan document.

Furthermore, at least two important implications for VCs are suggested by our findings. First, as novice VCs tend to be those employees in VC firms who are responsible for the initial screening of business plans, they are important gatekeepers whose decisions significantly impact the deal flow that more experienced VCs will evaluate at a later stage of the investment process. The divergence identified in team evaluations could prove problematic when novice VCs reject venture proposals on the basis of a negative assessment of criteria that experienced VCs would have evaluated more positively. As a result, VC firms may pass up interesting investment opportunities early on in the investment process. In this regard, our results also inform the VC community of the potential training needs of individuals entering the VC profession.

Second, individual VC firms can apply the method developed in this paper to develop a clearer understanding of their own decision processes. For example, deviations between agreed-upon investment policies and actual decisions can be uncovered and addressed. Furthermore, this method allows VCs to benchmark their own decision process (as regards teams) against that of other firms—a practice that could be particularly beneficial, as there seems to be room for improvement in the decision-making process of VCs (Shepherd & Zacharakis, 2002; Zacharakis & Meyer, 1998).

Implications for Future Research

Our results also offer several interesting insights for future research. First, as this study reveals significant differences in the team evaluations of novice and experienced VCs, it may be fruitful to extend this line of research by investigating whether experience also has a significant impact on the evaluation of other aspects of venture proposals. For example, it may well be that the assessment of business models (e.g., Amit & Zott, 2000) could be subject to experience effects. Whereas novice VCs may look at single components of business models (e.g., transaction efficiency), experienced VCs may place more weight on the fit of the various components, and thus may arrive at a better understanding of the overall value creation potential of the proposed venture.

Second, our findings reveal that future studies on VC decision making need to control for VC experience to avoid sample selection bias. Whereas biases arising from sample selection are troublesome in any kind of research, they seem to be particularly problematic in studies of VC decision making, as the findings of these studies are often interpreted as success factors in new firm creation.

Third, as our sample is comprised of a high share of less experienced VCs, future research could look more closely at VCs that have more than 10–14 years of experience and investigate whether this additional experience has an impact on team evaluations (or evaluations of other aspects of venture proposals, see earlier discussion). As noted previously, prior research indicates that decision effectiveness will decrease after a certain number of years in the VC profession.

Fourth, by exploring evaluation criteria this study focused on content issues in VC decision making. Smart (1999) investigated the methods VCs apply when assessing human capital (e.g., job analysis, work sample, reference interview) and thus complements our research with a tool-oriented process perspective. Future research could combine content- and process-oriented perspectives, and such research could also help in developing actuarial decision models (Zacharakis & Meyer, 2000).

Finally, this research was carried out in Germany and Austria, which might make the results specific to these countries. However, the maturing European VC scene in general is closely modeled on the U.S. example, and 36% of our interviewees work with U.S. venture capital firms. We tested whether the evaluation results differed between these respondents and the remainder of the sample but did not find any significant differences. Hence, we would not expect to see large differences between our results and a potential replication study conducted in the United States.

The perceived quality of the start-up team is of major importance in VCs' decision making. This paper adds to the growing literature on VCs' decision making by providing detailed evidence on their evaluation of start-up teams and by uncovering how the experience of VCs affects such evaluations.

REFERENCES

Adelson, B. (1981). Problem solving and the development of abstract categories in programming languages. *Memory and Cognition*, *9*, 422–433.

Amit, R. & Zott, C. (2000). Value creation in e-business. *Strategic Management Journal*, *22*, 493–520.

Bachher, J.S. & Guild, P.D. (1986) Financing early stage technology based companies: Investment criteria used by investors. In R. Ronstadt, J. Hornaday, R. Peterson, & K. Vesper (Eds.), *Frontiers of Entrepreneurship Research* (pp. 363–376). Wellesley, MA: Babson College.

Bagley, C. & Dauchy, C. (1999). Venture capital. In W. Sahlman, H.H. Stevenson, M.J. Roberts, & A. Bhidé (Eds.), *The entrepreneurial venture* (pp. 262–303). Cambridge, MA: Harvard Business School Press.

Beggs, S., Cardell, S., & Hausman, J. (1981). Assessing the potential demand for electric cars. *Journal of Econometrics*, *16*, 1–19.

Bygrave, W.D. (1997). The entrepreneurial process. In W.D. Bygrave (Ed.), *The portable MBA in entrepreneurship* (pp. 1–26). New York: John Wiley.

Díaz de León, E.D. & Guild, P.D. (2003). Using repertory grid to identify intangibles in business plans. *Venture Capital*, *5*, 135–160.

Dixon, R. (1991). Venture capitalists and the appraisal of investments. *OMEGA: International Journal of Management Science*, *19*, 333–344.

Franke, N., Gruber, M., Harhoff, D., & Henkel, J. (2006). What you are is what you like—Similarity biases in venture capitalists' evaluations of start-up teams. *Journal of Business Venturing*, *21*, 802–826.

Gagné, R.M. & Glaser, R. (1987). Foundations in learning research. In R.M. Gagné (Ed.), *Instructional technology: Foundations* (pp. 49–84). Hillsdale, NJ: Lawrence Erlbaum.

Gobbo, C. & Chi, M.T.H. (1986). How knowledge is structured and used by expert and novice children. *Cognitive Development*, *1*, 221–237.

Gorman, M. & Sahlman, W.A. (1989). What do venture capitalists do? *Journal of Business Venturing*, *4*, 231–248.

Goslin, L.N. & Barge, B. (1986). Entrepreneurial qualities considered in venture capital support. In R. Ronstadt, J.A. Hornaday, R. Petersen, & K.H. Vesper (Eds.), *Frontiers of entrepreneurship research* (pp. 366–377). Wellesley, MA: Babson College.

Hall, J. & Hofer, C. (1993). Venture capitalists' decision making criteria and new venture evaluation. *Journal of Business Venturing*, *8*, 25–42.

Hausman, J.A. & Ruud, P.A. (1987). Specifying and testing econometric models for rank-ordered data. *Journal of Econometrics*, *34*, 83–104.

Knowlton, B. (1997). Declarative and nondeclarative knowledge: Insights from cognitive neuroscience. In K. Lamberts & D. Shanks (Eds.), *Knowledge, concepts and categories* (pp. 215–246). Cambridge, MA: MIT Press.

Kozmetsky, G., Gill, M.D., Jr., & Smilor, R.W. (Eds.). (1985). *Financing and managing fast-growth companies: The venture capital process*. Lexington, MA: Lexington Books.

Larkin, J.H., McDermott, J., Simon, D.P., & Simon, H.A. (1980). Expert and novice performance in solving physics problems. *Science*, *208*, 1335–1342.

Lurigio, A.J. & Carroll, J.S. (1985). Probation officers' schemata of offenders: Content, development, and impact on treatment decisions. *Journal of Personality and Social Psychology*, *48*, 1112–1186.

MacMillan, I.C., Siegel, R., & Subba Narasimha, P.N. (1985). Criteria used by venture capitalists to evaluate new venture proposals. *Journal of Business Venturing*, *1*, 119–128.

MacMillan, I.C., Zemann, L., & Subbanarasimha, P.N. (1987). Criteria distinguishing successful from unsuccessful ventures in the venture screening process. *Journal of Business Venturing*, *2*, 123–137.

Marden, J.I. (1995). *Analyzing and modeling rank data*. London: Chapman & Hall.

Matlin, M.W. (2005). *Cognition* (6th ed.). New York: John Wiley & Sons.

Muzyka, D., Birley, S., & Leleux, B. (1996). Trade-offs in the investment decisions of European venture capitalists. *Journal of Business Venturing*, *11*, 273–287.

Poindexter, J. (1976). *The efficiency of financial markets: The venture capital case*. Unpublished doctoral dissertation, New York University.

Rea, R.H. (1989). Factors affecting success and failure of seed capital/start-up negotiations. *Journal of Business Venturing*, *4*, 149–158.

Riquelme, H. & Rickards, T. (1992). Hybrid conjoint analysis: An estimation probe in new venture decisions. *Journal of Business Venturing*, *7*, 505–518.

Robinson, R. (1987). Emerging strategies in the venture capital industry. *Journal of Business Venturing*, *2*, 53–77.

Roberts, E.B. (1991). *Entrepreneurs in high-technology—Lessons from MIT and beyond*. New York: Oxford University Press.

Sandberg, W.R., Schweiger, D.M., & Hofer, C.W. (1988). The use of verbal protocols in determining venture capitalists' decision processes. *Entrepreneurship Theory and Practice*, *12*(Winter), 8–20.

Shepherd, D. (1999). Venture capitalists' introspection: A comparison of "in use" and "espoused" decision policies. *Journal of Small Business Management*, *27*, 76–87.

Shepherd, D.A., Ettenson, R., & Crouch, A. (2000). New venture strategy and profitability: A venture capitalist's assessment. *Journal of Business Venturing*, *15*, 449–467.

Shepherd, D.A. & Zacharakis, A. (1999). Conjoint analysis: A new methodological approach for researching the decision policies of venture capitalists. *Venture Capital*, *1*, 197–217.

Shepherd, D.A. & Zacharakis, A.L. (2002). Venture capitalists' expertise: A call for research into decision aids and cognitive feedback. *Journal of Business Venturing*, *17*, 1–20.

Shepherd, D.A., Zacharakis, A.L., & Baron, R.A. (2003). VCs' decision processes: Evidence suggesting more experience may not always be better. *Journal of Business Venturing*, *18*, 381–401.

Shrader, R.C., Steier, L., McDougall, P.P., & Oviatt, B.M. (1997). Venture Capital and Characteristics of New Venture IPOs. In A.C. Cooper, J.A. Hornaday, & K.H. Vesper (Eds.), *Frontiers of Entrepreneurship Research* (pp. 513–524). Wellesley, MA: Babson College.

Siegel, R., Siegel, E., & MacMillan, I.C. (1993). Characteristics distinguishing high-growth ventures. *Journal of Business Venturing*, *8*, 169–180.

Silva, J. (2004). Venture capitalists' decision-making in small equity markets: A case study using participant observation. *Venture Capital*, *6*, 125–145.

Smart, G.H. (1999). Management assessment methods in venture capital: An empirical analysis of human capital valuation. *Venture Capital*, *1*, 59–82.

Spence, M.T. & Brucks, M. (1997). The moderating effects of problem characteristics on experts' and novices judgments. *Journal of Marketing Research*, *34*, 233–247.

Timmons, J.A. & Sapienza, H.J. (1992). Venture capital: The decade ahead. In D.L. Sexton & J.D. Kasarda (Eds.), *The state of the art of entrepreneurship* (pp. 402–437). Boston: PWS-Kent.

Tyebjee, T. & Bruno, A. (1981). Venture capital decision making: Preliminary results from three empirical studies. In K.H. Vesper (Ed.), *Frontiers of Entrepreneurial Research* (pp. 281–320). Wellesley, MA: Babson College.

Tyebjee, T.T. & Bruno, A.V. (1984). A model of venture capitalists investment activity. *Management Science*, *30*, 1051–1066.

Wells, W.A. (1974). *Venture capital decision making*. Unpublished doctoral dissertation, Carnegie Mellon University, Pittsburgh, PA.

Zacharakis, A.L. & Meyer, D.G. (1998). A lack of insight: Do venture capitalists really understand their own decision process? *Journal of Business Venturing*, *13*, 57–76.

Zacharakis, A.L. & Meyer, D.G. (2000). The potential of actuarial decision models: Can they improve the venture capital investment decision? *Journal of Business Venturing*, *15*, 323–346.

Zopounidis, C. (1994). Venture capital modeling: Evaluation criteria for the appraisal of investments. *The Financier ACMT*, *1*, 54–64.

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