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What you are is what you like - similarity biases in venture capitalists - evaluations of start-up teams

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What you are is what you like –
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Abstract

This paper extends recent research studying biases in venture capitalist's decision-making. We contribute to this literature by analyzing biases arising due to similarity between a venture capitalist and members of a venture team. We summarize the psychological foundations of such similarity effects and derive a set of hypotheses regarding the impact of similarity on the assessement of team quality. Using data from a conjoint experiment with 51 respondents, we find that venture capitalists tend to favor teams that are similar to themselves w.r.t. the type of training and professional experience. Our results have important implications for academics and practitioners alike.

Keywords: entrepreneurship, venture capital, start-up teams, similarity bias

1 Executive Summary

Studies on the investment processes of VCs and in particular on the criteria VCs employ to make their investment decisions have a relatively long tradition in entrepreneurship research, with the first studies ranging back to the 1970s (Zopounidis, 1994). These studies have produced a number of valuable insights into the VC decision process. The results are often interpreted as direct evidence on the long-term success factors of new firms, because professional investors who earn their money by investing in new firms are considered to possess much experience in distinguishing winners from losers (Riquelme and Rickards, 1992).

Though research gives key insights into the criteria used in the evaluation process, more recent studies reveal that previous results might be misleading due to (1) methodological shortcomings, as most research in this area relies on post hoc methodologies which typically suffer from problems of recalling past information (Shepherd and Zacharakis, 1999; Zacharakis and Meyer, 1998), and (2) biases in the decision process of VCs (Shepherd et al., 2003; Zacharakis and Meyer, 2000).

In this paper, we analyze a new form of bias, namely, systematic distortions of VC evaluations that derive from the similarity between rater (VC) and ratee (start-up team). In a nutshell, our research hypothesis states: "The higher the similarity between the profile of a venture capitalist and the profile of a start-up team, the more favorable the evaluation by the venture capitalist will be." Hence, this study in the field of entrepreneurship is the first to apply the "similarity-hypothesis" (Byrne, 1971) that has gained much interest in psychology, human resources management, and marketing to investment decisions by VCs.

In order to avoid some of the problems associated with post hoc methodologies, we use a conjoint data design which allows us to vary the characteristics of teams experimentally. We obtain preference rankings from 51 VCs regarding venture teams with particular characteristics. These rankings are analyzed using an ordered probit estimation model that includes team characteristics and similarity measures.

Our results give clear evidence that two of the five dimensions of similarity under consideration are statistically relevant. First, VCs with prior experience of working in either start-ups or large firms will tend to prefer teams with individuals coming from these backgrounds. And second, VCs who themselves have an engineering and managerial education tend to rate teams in which both competencies are present much higher than VCs who do not have this background. Other similarity dimensions (similarity in age, experience in leading teams and level of academic education) do not contribute to an explanation of the conjoint rankings in our data. However, our findings clearly show that similarity biases do play a significant role in venture capitalists' assessments of start-up teams. Hence, we are able to explain some of the variation occurring in venture capitalists' assessments on the basis of psychological theory.

Our results have important implications for future research and for practitioners:

- As to academic research, earlier studies of the VC evaluation process (with some notable exceptions) made the implicit assumption that VCs' ratings (of business plans, teams, etc.) concentrate around a certain "correct" evaluation, deviating from it by random errors only. Our results reject this assumption – deviations are not random, but contain systematic errors. Future research into the VC evaluation process should take this subjectivity into account. Specifically, this finding is relevant for research into success factors of start-ups, as they challenge the canonical practice of treating VCs' assessments as "objective" and unbiased success factors.

- Venture capital firms should be somewhat worried about the similarity biases we identified. It means that the persons evaluating business plans have systematically different preferences. As in our survey, in 55 percent of all cases only one person decides to reject or endorse the submitted business plans (thus to invite the team), this means that the screening process contains an unintentional component of randomness. This stands in sharp contrast to the extensive efforts undertaken to objectively assess the start-up potential in later steps of the evaluation process.

- For new venture teams, our results imply that it is not only the choice of the right VC firm that matters, but also the person who gets to read the business plan within the firm. Start-up teams should not be easily discouraged by a rejection, as it may be due to the fact that the team's and the

rater's profiles were strongly different, and may not say too much about the likelihood of being funded elsewhere.

2 Introduction

In the past three decades venture capital (VC) has evolved into a distinct industry within the financial services sectors of Western economies. As a major source of finance for new firms, particularly in high-technology industries, VC firms not only assume the role of risk financiers within the financial sector, but also serve as catalysts for innovation and renewal in the broader economy (Shepherd et al., 2000).

The success of VC firms is largely determined by their ability to predict new firm performance during a multi-stage evaluation process of investment proposals. Their special expertise in weeding out bad investment proposals is documented by research findings showing that VC-backed businesses achieve higher survival rates than non-VC-backed firms (Sandberg, 1986; Timmons, 1994). Hence, it is not surprising that the evaluation process of VCs has received much attention by the research community in entrepreneurship and finance (Wells, 1974; Poindexter, 1976; Tyebjee and Bruno, 1984; MacMillan et al., 1985; Sandberg et al., 1988; Muzyka et al., 1996; Zacharakis and Meyer, 1998), as it is supposed to give valuable insights on the criteria that distinguish successful from unsuccessful new firms.

However, more recent studies reveal that previous results might be misleading due to biases in the decision process of VCs (Shepherd et al., 2003; Zacharakis and Shepherd, 2001). This challenges the implicit assumption of earlier studies that evaluations by VCs can be treated as objective assessments of new venture quality disturbed only by a random error. Hence, research on the nature of these biases is elementary for our understanding of the relationship between VCs and new ventures, and of success factors of new firms. To date, research has been limited to biases due to the information processing *or* characteristics of the VCs (Shepherd et al., 2003; Zacharakis and Shepherd, 2001). This study is the first to systematically analyze similarity biases, emerging from an *interaction* between start-up team and VC characteristics.

We propose that some share of the heterogeneity of evaluations across venture capitalists is due to the similarity within the dyad. According to this hypothesis, venture capitalists will prefer (ceteris paribus) start-ups whose venture team members[1] share major characteristics with them. Thus, the discrepancies between the evaluation results of venture capitalists are conjectured not to be random, but to vary systematically with the personal profile of the rater and the characteristics of the team. Such biases can be explained on the basis of psychological theories. We focus in our analysis on the evaluation of venture team characteristics, and we do so for three reasons. First, research has shown that criteria related to the management team are consistently considered predominant in the evaluation process (Zopounidis, 1994). Second, the notion of similarity or dissimilarity between VC and the new venture is more likely to make sense with respect to team characteristics than, e.g., with respect to the business model of the new venture. Third, similarity with respect to team characteristics is relatively easy to observe for a VC (and for the researcher).

A sample of 51 VCs is used to test our hypotheses. In order to avoid some of the problems associated with *post hoc* methodologies, we use a conjoint data design which allows us to vary the characteristics of teams experimentally.[2] Each VC in our sample was asked to rank 20 hypothetical teams which were described in terms of seven characteristics, in a way that models simplified team descriptions in business plans. The resulting rankings are analyzed using ordered probability models.

We find clear evidence supporting our hypothesis: two of the five dimensions of similarity under consideration are statistically significant. First, VCs with prior experience of working in start-ups tend to prefer teams with individuals who had gathered professional experience in new ventures. In turn, VCs who had been working only for large firms tend to evaluate higher those teams that have prior experience in large firms. And second, VCs who themselves have an engineering and managerial education will tend to rate teams in which both competencies are present much higher than VCs who

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[1]   We will use the terms venture team, managing team and founding team as synonyms in this article.

[2]   Conjoint analysis has been used in recent studies in this field, e.g., by Shepherd and Zacharakis (1998) who argue that this approach improves the validity of research into the decision making practices of VCs.

do not have this background. VCs who have only management training give relatively high ratings to teams whose members' training has focused on management. Our findings clearly show that similarity biases do play a significant role in venture capitalists' assessments of start-up teams. Hence, we are able to explain some of the variation occurring in venture capitalists' assessments on the basis of psychological theories.

Our results have important implications for academics and practitioners alike. Research should try and correct for similarity biases when using VC evaluations as indicators for new venture success factors. VCs will want to avoid these biases in order to arrive at an undistorted evaluation of team quality. While a similarity bias might have a positive effect *if* the rater subsequently becomes the team's coach and *if* this similarity simplifies collaboration (which is debatable), we find that, certainly in big VC firms and in early stages of the evaluation process, the initial rater is in most cases not the person who conducts the follow-up relationship. Hence, the bias does have negative effects for VCs. For start-ups, our results imply that it matters considerably who in the VC firm reads the business plan, and that it will be worth the effort to identify the most suitable (i.e., most similar) contact person.

The remainder of the paper is organized as follows: In the next section, research on the VC decision process is presented along with findings on similarity biases in decision making in other areas. Section 4 discusses the hypotheses guiding this study and section 5 describes the research design. In section 6, the empirical findings of this research are presented in some detail. A discussion of the implications of our results in section 7 concludes this paper.

3   Previous research

3.1   *The venture capital investment decision process*

Studies on the investment decision processes of VCs and in particular on the criteria VCs employ to make their investment decisions have a relatively long tradition in entrepreneurship research, with the first studies ranging back to the 1970s (for an overview see Zopounidis, 1994). These studies have produced a number of valuable insights into the VC decision process. The results are often interpreted as direct evidence on the long-term success factors of new firms, because professional investors who

earn their money by investing in new firms are considered to possess much experience in distinguishing winners from losers (Riquelme and Rickards, 1992).

Thus, the underlying premise of this line of research has been that venture capitalists are able to evaluate the success potential of start-ups *objectively*. "Objectivity" here means that their estimation is unbiased, i.e., on average, the VC's assessment predicts the actual success of the start-up correctly, leaving aside some random error. This paradigm of objective VC financing decisions forms the implicit or explicit basis for studies that operationalized expected success of start-ups by using start-up evaluations made by VCs (Khan, 1986). The rhetoric of the venture capital industry backs the assumption of objectivity as financing decisions usually are affirmed as emerging from a clearly defined multi-stage evaluation process, starting with the appraisal of a business plan and including a thorough due diligence of the proposed venture. Several arguments can be brought forward to support this notion. First, the evaluation process and the resulting selection decisions are crucial to the success of a VC firm (Zacharakis and Meyer, 1999) and usually also to the individual VC's personal income. Thus, both the VC firm and the individual evaluator have a strong *incentive* to avoid any form of bias. Second, the evaluator should also be *able* to avoid such bias, as VCs typically are highly trained professional investors (Barry et al., 1990).

However, research in other fields has pointed to the fact that managerial judgment and decision making is not perfectly rational, but boundedly rational (Cyert and March, 1963; Simon 1955). In particular, scholars from organization science have identified several factors which explain deviations from a purely rational decision making process (Busenitz and Barney, 1997). These factors include the high costs associated with the pursuit of a purely rational decision process (Simon, 1979) and the information-processing limits of human beings (Abelson and Levi, 1985). A particularly important class of factors that inhibit perfectly rational decision making consists of biases and heuristics of decision makers (Kahneman and Tversky, 1982; Kahneman et al., 1982; Hogarth and Makridakis, 1981;, Schwenk, 1988). Biases prevent decision-makers from correctly processing information (Tversky and Kahneman 1974), yet, they are not *per se* evident, as their occurrence, magnitude as well

as their consequences are dependent on the nature of the decision task (Zacharakis and Shepherd, 2001).

Research on the VC decision making process has only recently begun to study potential biases. Zacharakis and Shepherd (2001) analyzed new venture investment decisions and found that 96% of 51 participating VCs exhibited a significant overconfidence bias which affected their decision accuracy negatively. Shepherd et al. (2003) studied in how far experience impacts a VC's evaluation process in a sample of 66 Australian VCs. Their results show that increasing experience is beneficial to VC decision making, yet only to a certain point – approximately 14 years of experience –, where additional experience actually has a negative marginal effect on reliability and performance.

To date, studies are restricted to simple, "one-dimensional" biases only. They identify VCs' characteristics and argue that these *generally* impact their evaluation decisions. Although some important deficiencies of VC decision making processes could be detected this way, the underlying rationale is still rather mechanistic as VCs are assumed to react in a stable manner, e.g., by being overly confident. If this was true, biases could be identified and corrected in a relatively easy way, thereby improving the quality of financing decisions, and preserving implications for research on the success factors of new ventures.

A contribution of this paper is to introduce interaction biases into the evolving literature on VC decision-making. It is no longer assumed that VCs' characteristics impact all their evaluation decisions in the same manner. Instead we argue that the interaction of the venture capitalist and the object at issue matters: *specific* VCs will evaluate *specific* start-ups in a systematically different way. The *similarity* between the evaluator and the members of the start-up team will impact the VC's evaluation decisions.

3.2   The similarity effect

"Birds of a feather flock together" is the saying that illustrates the basic hypothesis of this paper. The insight *per se* is not new.[3] It has, however, been confined to psychology and hardly been incorporated into behavioral economics or management studies. One of the first to systematically analyze this phenomenon was the social psychologist Byrne (1971). He proposed a "similar-to-me" hypothesis: according to his theory, individuals rate other people more positively the more similar they are to themselves (or the more similar the rater believes they are). To understand the effect, psychologists usually draw upon three different theoretical backgrounds: (1) learning theory, (2) self-categorization theory, and (3) social identity theory. These will be addressed in turn.

(1) Byrne (1971) presented a reinforcement model based on *learning theories* in which similarity is perceived as being rewarding and dissimilarity works as a negative reinforcement. Perceived similarity causes an affective reaction (i.e., interpersonal attraction) which in turn impacts the evaluative response (see Lefkowitz, 2000, for an overview of empirical research supporting this notion).

(2) *Self-categorization theory* implies that a person's self-concept is based on the social categories he places himself in (e.g., age, gender, education etc.) and that he strives for having a positive self-identity (Jackson et al., 1991; Turner, 1987). This desire causes him to have a preference for those who are similar with respect to the social category on which he bases his identity. One should note that this theory suggests that no actual interactions are necessary to provoke such a bias.

(3) A related explanation is offered by *social identity theory* (Tajfel, 1982). It argues that people wish to belong to a group as this leads to the positive feeling of social identity. The assignment to a specific group (which can also be a "virtual" group as, e.g., "we engineers") allows for in-group/out-group comparisons which are biased towards the own group (Bass and Dunteman, 1963; Dustin and Davis, 1970; Brewer, 1979). Duck (1977) endorsed this by proposing a "filtering model," suggesting that relatively superficial levels of similarity (e.g., same occupation) influence attraction and

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[3]   Goldstein (1980) cites Aristotle and Spinoza already describing such a relationship.

subsequent judgmental evaluations particularly at early stages in the acquaintance process. Conversely, "deeper" levels of similarity (such as personality) can be associated with attraction only after considerable information about the person to be evaluated has become available (see Harrison et al., 1998, for an empirical test).

The "similar-to-me" hypothesis could be confirmed for many situations outside business life (e.g., marriage decisions[4]). It has also been successfully applied to some management fields that have a long tradition of psychologically-rooted reasoning, such as human resources management and marketing. For example, Lichtenthal and Tellefsen (2001) provided an overview of studies that explain the different outcomes of buyer-seller relationships by their actual and perceived similarity. Homburg et al. (2002) studied the effect of similarity on marketing channel relationships and found that relationship effectiveness is positively affected by similarity. There is considerable evidence that similarity affects the outcome of employment (e.g., Pfeffer, 1983) and graduate selection interviews (Anderson and Shackleton, 1990). Supervisors' ratings of the effectiveness of subordinates are also affected by similarity biases (e.g., Tsui and O'Reilly, 1989).[5]

As discussed above, the paradigm of objective financing decisions of VCs has been challenged only recently. Thus, it may not be astonishing that to date no study of similarity effects has been carried out in the realm of VC financing decisions.

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[4] See Angier (2003) for a summary of recent studies from evolutionary biology.

[5] In some situations there might be limits to similarity-effects. For example, when people are identical or have the feeling that others are closer to their "ideal self" than they are themselves, this may not lead automatically to attraction (e.g, Herbst et al., 2003). Also, in some situations (e.g. when complementary characteristics are desirable) opposites (rather than similar individuals) attract each other (Dryer and Horowitz, 1997). We cannot exclude the possibility that such effects impact the VC – start-up team relationship, as we are clearly just starting to explore the importance of similarity in this context.

4 Hypotheses

In our study, we want to test for similarity biases in the venture capital decision making process as described in section 3.1. Even though similarity effects have been found in other fields, it is not obvious that significant and sizeable effects can be detected for VCs and venture teams. After all, as was shown in section 3.1, there are indeed good reasons to assume that the VC decision process is rational to a very high degree. In that regard, the deck is stacked against finding evidence in favor of our hypothesis. However, if similarity biases are present, describing and accounting for them is important, since earlier empirical results may be incomplete or even unreliable. If venture capitalists have a tendency of financing entrepreneurs "in their own image", existing advice to entrepreneurs and firmly held research results may be in need of revision or amendment.[6]

"Similarity" can be defined along a number of dimensions. In our study, we focus on the evaluation of the start-up *management team characteristics* for three reasons. (1) Research has shown that criteria related to the management team are consistently considered predominant in the VC evaluation process (Zopounidis, 1994).[7] Compared to the perceived quality of the start-up team aspects such as market attractiveness, cashout potential, or product characteristics are rated as of lower importance. (2) The notion of similarity or dissimilarity between start-up team and VC makes more sense with respect to personal characteristics than, e.g., with respect to the start-up's business model or industry. (3)

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[6]   A VC's preference for founders whose profiles resemble his or her own would be rational if (a) such similarity simplified future collaboration between the VC and the start-up in case of financing, and (b) there was a good chance that the rater became the coach of the future portfolio firm. However, given the size of VC firms assumption (b) will in most cases not be fulfilled. We comment in detail on conjecture (a) as an alternative, but unlikely explanation of our results in section 6 of the paper.

[7]   In our research, we can confirm this finding. When asked to rate the relative importance (a constant number of 12 points should be distributed among the three choices according to their subjective importance), the 51 venture capitalists placed a mean value of 3.2 on the product idea, 3.4 on the market, and 5.4 on the venture team. The differences between these means in two sided t-tests are highly significant (product to team ($t= -8.41$, $p<0.0001$, market to team ($t=-7.32$, $p<0.0001$)).

Similarity or dissimilarity with respect to team characteristics is relatively easy to detect for a VC. It should be noted that other aspects of the start-up can also be subject to similarity impressions. Any business plan reveals potentially similar preferences, appraisals of future development of markets, argumentation patterns, conclusions etc. But these are neither as likely to be observed by the VC nor to be measured easily in an empirical study.

Thus we state as our basic hypothesis:

> *The higher the similarity between a venture capitalist and the members of a start-up team,*
> *the more favorable the evaluation by the venture capitalist will be.*

Theories of self-categorization and social identity suggest that this general hypothesis applies to dimensions only that are salient and of subjective importance to the evaluator (e.g., Turner, 1987). Only then do individuals perceive others either as members of the same category as themselves or as members of a category different from their own (Van Der Vegt et al., 2003). The identification of such dimensions is difficult as an individual's lens for sense-making and signification varies across situations, institutional contexts, and over time (Smircich, 1983).

In the following, we transform our basic hypothesis into testable (*ceteris paribus*) hypotheses. Our choice of dimensions with respect to which we formulate similarity hypotheses is guided by three considerations. First, as will be laid out in section 5.2, we focus on a particular stage of the evaluation process, namely the assessment of the written business plan. Hence, we only take those venture team characteristics into account that appear in the team description as part of the business plan. Our measures of similarity need to relate to these variables then. Second, we only include dimensions for which there is reason to believe that they are salient and important to the venture capitalists. And third, since we use a conjoint technique for our data collection, we have to keep the thought-experiments manageable for the interviewees. We therefore have to focus on a limited number of team attributes.

Taking into account the above-mentioned considerations, we conducted seven exploratory interviews with venture capitalists, analyzed several dozens of real business plans, and evaluated the existing literature. This led us to choose the following dimensions of similarity for our study: age,

educational background, field of training (management or technical), prior professional experience (large firm or start-up) and experience in leading teams in previously held positions. These dimensions give rise to the following five hypotheses:

Hypothesis 1:   VCs will prefer start-up teams that are similar to themselves with respect to age.

Hypothesis 2:   VCs will prefer teams in which their own level of education is shared by a large number of team members.

Hypothesis 3:   VCs will prefer teams in which their own field of training (management or technical) is shared by a large number of team members.

Hypothesis 4:   VCs will prefer teams in which their own professional background (start-up vs. large firm) is shared by a large number of team members.

Hypothesis 5:   VCs will prefer teams in which their own experience in leading teams is shared by a large of number of venture team members.

We also include in our analysis two team characteristics that do not lend themselves easily to the formulation of similarity hypotheses – the extent of experience in the industry in which the start-up is assumed to be founded, and the extent to which the team members are acquainted. We do include these variables because the team descriptions used in the conjoint analysis, even though they are necessarily simplified, need to be realistic. This implies that they must contain the most important team characteristics.[8]

5   Research design

5.1   The sample

For the present study, a total of 51 interviews were conducted between December 2001 and April 2002 in 26 different VC firms, with individuals actively involved in the evaluation of business plans.

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[8]   Interviewees in a conjoint analysis typically find it difficult to rate objects that are described in an unrealistic or incomplete manner.

The VC firms were located in Munich, Berlin and Vienna. The description in the Appendix shows that our sample contains VC firms of different sizes, degree of internationalization, and industry focus. The focus of the respective VC funds is on telecommunication, software, and e-/m-commerce rather than on biotechnology, since the VC firms were chosen to match our hypothetical business model (see below).

5.2   Conjoint approach – the interviews

In order to test our hypotheses, we had to collect two types of data: (1) information on VC characteristics and (2) information on VC evaluation of start-up teams, and to operationalize our similarity measures from the collected VC and team data.

(1) Information on VC characteristics

Interviewees were asked about their age, education, professional experience, and experience as a venture capitalist. Those questions in our questionnaire that pertain to the study of similarity biases are shown in Figure 1. In Table 1, we describe the operationalization of VC characteristics as we employ them later in the construction of similarity variables.

Please insert figure 1 about here

Please insert table 1 about here

In addition, information was collected about the venture capital firm covering its size, funds volume, specialization on industries or financing stages, and its evaluation process. An aggregate description of the data obtained is provided in the Appendix.

(2) Conjoint design

In collecting information on VC evaluation of start-up teams, we focus on an important early step in a venture capitalist's assessment of a new venture, namely, the appraisal of the business plan. During this stage of the evaluation process, a decision has to be made whether to reject the venture proposal, or to pursue it further and to invite the venture team for a presentation (Dixon, 1991; Bagley and Dauchy, 1999). With more than 80% of new venture proposals typically being rejected during this initial stage (Roberts, 1991), the business plan is a particularly crucial document for venture capitalists and new venture teams alike.

One central piece of the business plan is the team description. This presentation of the venture team is the focus of our analysis. There are four reasons for this choice. First, as was argued above, the initial assessment of the business plan is decisive for the project's further fate. Second, a venture capitalist's criteria in evaluating a team depend on the stage of the evaluation process, for reasons of observability. For example, the willingness of team members to cooperate within the team cannot be observed from the written business plan, and qualities such as perseverance and stress resistance will only be observable in the long run. Hence, when studying venture capitalists' choice criteria it is important to clearly identify the step in the decision process where these criteria are applied. Third, we focus on this particular step because the team characteristics that are relevant here are comparatively objective, unlike, e.g., personal fit between team members (which becomes relevant in later stages). Fourth, the evaluation of the start-up team as described in the business plan can very well be simulated using conjoint analysis (see below). While in most other instances conjoint cards describe some real-world object that the interviewee is asked to imagine, in our case the team description on the conjoint card is of the same nature as the object itself, namely, the team description in the business plan. Hence, apart from the necessary simplification of the team description, the conjoint approach in our analysis is unusually realistic; the criticism that "paper ventures" lack external validity (Shepherd and Zacharakis, 1999) does not apply.

There are several other reasons why a conjoint approach is suitable for the question at hand, and why it is superior to commonly used *post hoc* methods which collect data on VCs' self-reported decision policies (Shepherd, 1999; Shepherd and Zacharakis, 1999; Zacharakis and Meyer, 1998). In

retrospective surveys, venture capitalists may intentionally bias the result, or they may lack sufficient insight into their own decision processes to report them properly. The first problem is alleviated by the conjoint approach, since the link between responses and final results is less obvious; the second problem is actually solved by this approach, since we do not require the VCs to report a model of their own behavior.

The evaluation of a start-up team by a VC depends on the type of the venture. For example, a biotechnology venture team most likely requires scientists from molecular biology, while for an online service, founders with management and information technology knowledge are needed. Hence, we had to define the type of business that the team under consideration was about to start with some degree of specificity. On the other hand, too specific a description of the venture would have implied the risk that individual interviewees identified the hypothetical start-up with a particular past experience; this would have compromised the external validity of our analysis. After a number of exploratory interviews on that matter we chose a description of the hypothetical venture that indicated the type and maturity of the venture, while remaining sufficiently general (see Figure 2). To ensure comparability, the venture description was identical for all teams.

Please insert figure 2 about here

The variables used in the team descriptions and their realizations are listed in Table 2. Given the high level of professionalism of our interviewees, it seemed feasible to use a full profile rank order method. Employing a reduced set plus two hold-outs led to 20 conjoint cards. Intuitively, this roughly amounts to randomly combining the various realizations of each of the seven attributes.

We communicated to the interviewees that the team consists of four members. We chose this team size for several reasons. First, this was found to be a very common team size. Then, varying the number of team members did not seem to be too important, since VCs would often support the search for individuals to fill vacant positions in a venture team. Finally, the even number of team members

means that if the team is described as "some management, some engineering education", then this could easily be interpreted as an even split between the two subgroups.

Please insert table 2 about here

A pre-test, where five venture capitalists were interviewed, confirmed that attributes and parameter values on the conjoint cards were well chosen, and that the task to rank 20 hypothetical teams was manageable. The initial business plan description was found to be too specific; it was corrected accordingly prior to the main survey. Structured interviews were then conducted by one interviewer who was present during the whole interview. During the interviews, none of the participants encountered any problems in ranking the 20 cards with the description of team characteristics, which were presented to all participants in the same order. In order to keep the interviews short and manageable, we asked for ordinal, not metric information on the interviewees' team evaluations.

(3) Operationalization of similarity variables

In order to test our hypotheses, we had to operationalize similarity with respect to a number of dimensions, based on the data we had collected from our interviewees and the team descriptions. The similarity measures which we use in the empirical tests of these hypotheses are defined as follows.

We measure similarity in age (Hypothesis 1) via two dummy variables. The first one is coded as one if the VC rater is older than 40 and the team members are between 35 and 45 years old (zero in all other cases). The second dummy variable is coded as one if the VC rater is younger than 30 and all team members are in the age bracket between 25 and 35 years, and again zero in all other cases.

Similarity in the level of university education (Hypothesis 2) is somewhat more difficult to define, since all of the interviewed venture capitalists have a university degree. In order to test for potential effects of similarity in education, we use the following operationalization. We defined one dummy variable which was coded as one if the first degree of the VC had been an apprenticeship training and if the simulated team did not contain any individual with university training (zero in all other cases).

We then defined another dummy variable for those cases in which all team members were supposed to have university training and the VC herself had obtained a doctorate degree (again coded one in this case, and zero in all other cases).[9] Since none of the four VCs who had initially gone through apprenticeship training had acquired a doctorate, the two variables do not overlap.

Similarity in the field of education (Hypothesis 3) is measured using three dummy variables. The first one is coded as one if the VC and all team members have technical training only, and as zero in all other cases; correspondingly, the second one assumes the value of one if the VC and all team members have management training only, and zero in all other cases. The case of complementary competencies (VC has both technical and management training and the team includes some team members with management and some with technical backgrounds) is a separate dummy variable.

Similarity in prior job experience (type of firm) (Hypothesis 4) is again operationalized by identifying three groups of observations where similarity is most pronounced. The first variable identifies cases where the VC rater had been working in start-ups only before joining the VC industry, and where the members of the team had start-up experience only. The second variable characterizes analogous cases where the experience of the VC and the team members comes from working in large firms. Finally, we generated one variable for those cases in which both the VC and the team members had obtained experience in start-ups and large firms.

We measure similarity in team leadership experience (Hypothesis 5) accordingly by identifying one group of observations for which both the VC and all team members have only weak experience in personnel responsibility; and another group for which both the VC and all team members have extensive experience of this type.

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[9] Doctoral degrees are more common in continental Europe than in Anglo-Saxon countries. In our sample of 51 VCs, 11 of them had obtained a doctorate degree. In the presence of similarity biases, this group would show more affinity towards teams consisting of members who all have academic training.

6   Empirical results

Our objective is to describe the impact of our team variables and of the similarity measures on the assessment that a team in our conjoint experiment receives. The assessments are measured as rankings, i.e., in ordinal form. Before we undertake a multivariate analysis of our data, we briefly consider some descriptive statistics. For each of the respondents, we determine the cases that were ranked in the top quartile (i.e., which had been given one of the upper five ranks). In Table 3, we tabulate the percentage of the overall number of cases with the respective realization of feature x that were ranked in the upper quartile. For example, there are six teams whose members are between 35 and 45 years old. Of these six teams, on average 2.24 (37.3%) were ranked in the top quartile. Within team characteristics, we order the realizations by their share of top quartile ranks. The second column contains the preferred realization, the third column the second-best, and the forth column the least preferred realization. This tabulation is a first indication of which realizations lend themselves to successful outcomes. In a sense, the realizations listed in the second column of Table 3 describe the "dream team" which combines all of the preferred characteristics. We will use these realizations in the multivariate analysis to define the reference groups for our dummy variables describing team characteristics.

Please insert table 3 about here

We describe now our multivariate analysis in which we try to test for similarity effects, once the impact of team characteristics has been taken into account. Our estimation approach relies on a latent variable approach. We assume that venture capitalist k assigns team i a metric indicating the VC's willingness to finance the team. We model the metric that a team receives as a continous function R_{ki} of our seven basic team variables ($j=1,...,7$) – which enter the equation with two realizations D_{j1} and D_{j2} each - and twelve similarity variables S_m ($m=1,...,12$) as discussed before. The metric can then be written as:

$$R_{ki} = \beta_0 + \sum_{j=1}^{7}\left(\beta_{j1}D_{j1i} + \beta_{j2}D_{j2i}\right) + \sum_{m=1}^{12}\gamma_m S_{mi} + \varepsilon_{ki}$$

The error terms are assumed to be i.i.d. within each VC (across team cases), but not necessarily independent across VCs (within team cases). The ratings that the 20 simulated teams receive may very well be affected by unobservable interpretations of a particular team constellation which are shared across the rating VCs. In this case, one would expect that corr(ε_{ki}, ε_{li}) ≠ 0. We do not observe the metric R_{ki} itself, but instead the ranking information from our conjoint experiment. From the rankings, we compute the ranking quartile in which team i was put by the venture capitalist. We then apply an ordered probit model[10] to the quartile information. The potential correlation across VCs (within teams) is taken into accout by representing our data as a cluster sample and employing a Huber-White variance-covariance estimator in order to obtain conservative statistical inference results.[11] We can use our maximum-likelihood estimators to test the hypotheses derived in section 4 and to retain a preferred specification which includes the similarity measures that are statistically relevant. Finally, we compute the effect sizes of our variables, since the coefficients in the ordered probit cannot be interpreted easily.

Since our right-hand side variables are discrete binary regressors, we need to identify reference groups within each dimension. We take the preferred variable realizations displayed in Table 3 as our

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[10] See Davidson and MacKinnon (1993, ch. 15) for a detailed description of binary and ordered probability models. We experimented with alternative specifications, e.g., (i) simple probits using top quartile status as the dependent variable and (ii) ordered probits using the top five ranks and the three subsequent quartiles as the ordinal dependent variable. Qualitatively, the results are similar and the inference results are the same as the ones reported here. Using specficication (ii), i.e., taking the exact ranking in the top quartile into account leads to an improvement of information used, but since we need to estimate a larger number of threshold parameters at the same time, the overall effect on the precision of our estimates is neutral. These estimates are available upon request. The choice of ordered probit over other types of ordered probability models is arbitrary. Using ordered logit estimators yields qualitatively similar results, which is not surprising, since the logit and the normal distribution are very similar. Moreover, in a small sample as the one here we cannot test empirically which distribution is the better choice.

[11] For the estimation, we employ the ordered probit estimator in STATA 8.0.

reference cases. The coefficients for our dummy variables will then indicate the extent to which the team's success is reduced by deviating from the "dream team" characteristics. Therefore, we should expect negative coefficients for all of the respective dummy variables. As to our similarity measures: the base case is a combination of venture capitalist and team to be rated without any similarity as measured by our twelve dummy variables discussed at the end of section 5.

The estimation results are displayed in Table 4. A positive coefficient in these results always implies a positive effect, i.e., an improvement of a team's ranking. To discuss the effect size of our variables, we list in column (4) the marginal effect of the respective variable on the probability of being in the top quartile of the rankings. The marginal effects are based on the specification in column (3).[12]

We first discuss the results for our team characteristics variables. While these results are not the primary focus of the paper, they are illustrative of the advantages of the conjoint approach followed in this paper. Consider the estimates in column (1) of Table 4. We achieve a reasonable pseudo-R-squared value[13] of 0.227 with this estimate, and we easily reject the hypothesis that all coefficients are jointly equal to zero. As we expected, all coefficients carry negative signs, indicating that the reference categories of our dummy variables do indeed characterize the "dream team" configuration. All but one of the coefficients are significant at the 5 or 1 percent levels. The multivariate results confirm the descriptive evidence summarized in Table 3: VCs prefer to see teams with older (i.e., more experienced) founders *all* of whom have an academic education, experience in the relevant industry

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[12] Closer inspection of the data shows that there is no major multicollinearity problem. The correlation coefficients between the team characteristics appearing in our team descriptions are extremely low and never exceed 0.15 which is due to our conjoint design. The correlation between similarity variables and team characteristics can be higher; but the maximum that we observe is a Pearson product-moment correlation coefficient of 0.432 for the correlation between the variable "VC and team with experience mostly in large firms" and "team members' prior job experience mostly in large firms".

[13] This measure cannot easily be compared with the R-squared from an OLS regression. If we simply used OLS to regress the rank position on the independent variables used in column (2), the R-squared would be 0.542.

and experience in leading teams, a mixed background in the field of training and experience in both start-ups and large firms.

Please insert table 4 about here

Our hypotheses state that particular VC raters will prefer particular teams if there is similarity between the rater and the team. We would therefore expect to see positive significant coefficients for our similarity variables if such effects were present. Such a result would clearly indicate that the assessments of different VC raters will be influenced by their own experience and background. In column (2) we introduce all of our twelve similarity measures into the regression in order to test this hypothesis. There is a significant gain in explanatory power – performing a Wald test on the hypothesis that all similarity coefficients are jointly equal to zero is clearly rejected ($\chi^2(12)$=55.98, p<0.0001). But the results also show that only two of the five subgroups of similarity variables carry coefficients that are individually significant at the 10 percent level or better. Similarity in age (Hypothesis 1), in level of education (Hypothesis 2) and in experience in leading teams (Hypothesis 5) do not appear to matter statistically. We perform Wald tests for each of the groups and for all three groups jointly.[14] We cannot reject the hypothesis (either by group or jointly) that these similarity variables do not matter statistically. Conversely, we also test whether the remaining two blocks of similarity variables (field of education, Hypothesis 3, and type of professional background, Hypothesis 4) have any statistical relevance. Again using Wald tests derived from the results in column (2), we compute test statistics for Hypothesis 3 ($\chi^2(3)$=14.41, p<0.001) and Hypothesis 4 ($\chi^2(3)$=21.27,

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[14] The test statistics are: for similarity in age (Hypothesis 1) - $\chi^2(2)$=0.89, p=0.641; for similarity in type of education (Hypothesis 2) - $\chi^2(2)$=0.10, p=0.952; for similarity in leadership experience (Hypothesis 5) - $\chi^2(2)$=1.13, p=0.568. The joint test yields a chi-squared test statistic of 8.44 with 6 degrees of freedom (p=0.208).

p<0.001) which demonstrate the statistical relevance of these two types of similarity measures. The joint test yields a chi-squared test statistic of 46.72 with 6 degrees of freedom (p<0.001).

As indicated in the hypotheses section, it is difficult to assess a priori which dimensions are salient and important to VCs. Hence, it is not surprising that not all hypotheses are supported. It is interesting to note, however, that the dimensions of similarity that are statistically relevant differ from those that are not. Both the field of education and the professional background are (a) freely chosen by the respective person and (b) in most cases constant over time. In contrast, age and personnel responsiblity are not a matter of choice, and they vary over time. It seems in alignment with theory of social identity that stable and choice-based variables are more important for constituting similarity bonds between individuals than characteristics that are contingent on the environment (Garza and Herringer, 1987). This finding may provide an important hint for further tests of the similarity hypothesis.[15]

Note also that all coefficients that are individually significant carry a positive sign. This is consistent with our expectations – after all, we stated in our hypotheses that increased similarity would lead to an improvement in the ranking of the respective team.[16] The fact that we do not find any negative, statistically significant coefficients supports our theoretical interpretation of similarity biases quite nicely. Suppose that because of her own experience, a venture capitalist can assess a team sharing some characteristics with the VC more precisely than other VCs who do not have this particular experience. Then we would expect that some of the assessments made by the well-informed VC would be more positive, and some more negative than those of other VC raters. It is the very fact that our significant similarity effects are all associated with positive coefficients that makes it extremely difficult to argue that such effects emerge from a rational and completely logical assessment

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[15] Following this logic, we would also expect the level of education to show a significant effect. However, as we pointed out before, our sample provides little variation in this variable, which at least partly explains the lack of significance.

[16] Although we have a directional hypothesis, the level of significance indicated in Table 4 for the individual variables is based on two-sided tests.

of team quality. In our view, they constitute strong evidence supporting the notion of important similarity biases in the assessment process.[17]

Since the inclusion of a large number of statistically irrelevant variables is going to affect the overall precision of our estimates, we restrict the specification in column (4) to the basic team characteristics and those similarity variables that were jointly significant in column (3). Indeed, estimating this specification gives us a modest gain in precision, but the estimated coefficients differ only marginally from those displayed in column (3). Now, five out of six of the remaining similarity variables carry significant, positive coefficients (with p<0.1).[18]

In column (4) of Table 4, we finally compute the effect sizes associated with our variables. In order to have an intuitively appealing interpretation, we compute the average change in the probability of being among the top five teams associated with switching from the respective reference group to the group indicated by our respective independent variable. All other variables are held constant so that the computed marginal effects differ across observations. We report the average of the observation-specific marginal effects. To give an example, our reference case for team age is a team with members between 35 and 45 years old. Holding every other variable at their empirical values, a shift to a team with members who are between 25 and 45 years old reduces the probability of being in the top quartile of teams on average by 11.3 percentage points. A shift to a more heterogeneous team whose members

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[17]   As one referee suggested, it is possible to differentiate our reference groups w.r.t. the dissimilarity between VC and team. When we introduce – for each of the five groups of similarity variables – a set of dissimilarity variables (in total 10 additional variables), we find them to be insignificant jointly as well as individually. We need to interpret this result cautiously, since we have only ordinal measures of similarity. The statistical insignificance of all dissimilarity regressors may be due to our operationalization. Nonetheless, we find it worthwhile to study the potentially differential impact of similarity and dissimilarity in future work.

[18]   The test statistics for this specification are: for similarity in field of training (Hypothesis 3) - $\chi^2(3)=9.64$, p=0.020; for similarity in type of professional background (Hypothesis 4) - $\chi^2(3)=15.94$, p=0.001. The joint test yields a chi-squared test statistic of 28.51 with 6 degrees of freedom (p=0.001).

are between 25 and 45 years old causes a slightly smaller average reduction of 8.6 percentage points. Thus, the marginal effects in column (4) describe, for an otherwise average team, the "penalty" for deviating from the optimal realization of the respective characteristic.

For our purposes, the team variables themselves are not the primary focus. We would like to see if the statistically significant results regarding our similarity effects also translate into notable effect sizes. For some of the similarity variables, this is indeed the case: in cases where the VC and the team have received training in technical fields and management, the likelihood of being in the top quartile of teams increases by 7.5 percentage points. Similarly, in cases where the VC and the team members have had professional experience in startups only, the teams are awarded a 7.3 percent bonus, after taking all other variables into account. These effect sizes are hardly trivial. Note that teams whose members have management training only receive a penalty of 24.5 percentage points (relative to the optimal configuation). But in cases where the VC shares this disadvantage, the team receives a bonus of 5.0 percentage points. Similarly, a configuration of VC and team members both having solely a large-firm background results in a 3.7 percentage point gain for the team. We can conclude that the effects associated with the similarity biases are somewhat smaller than those for the basic team variables, but they do have a significant and strong effect on the overall selection of teams by venture capitalists.

To summarize, we find a consistent tendency for some similarity measures to have a positive effect on team assessments. We do not find any evidence that similarity measures have a negative impact on team ratings. As we pointed out, this asymmetry in our results is very important for our interpretation. While our evidence appears to be stable in statistical terms, the estimated rank movements also show that similarity effects are smaller than the impact of the major team characteristics, but by no means unimportant. The existence of these similarity effects brings about a number of implications which we discuss in the final section.

7 Discussion and conclusion

The purpose of this research study is to test if VC evaluations of start-up teams suffer from a similarity bias. The results of our study confirm the existence of this distortion due to the interaction of characteristics of VC and start-up team. The more closely the team members' profiles resemble that of the VC with respect to two important dimensions, the better – on average – the team will be rated. We find a rather strong similarity bias for the type of education: VCs who had received training both in engineering and in business gave a significantly higher rating than other VCs to teams whose members have an education partly in engineering, partly in business. Similarly, VCs who had received training in business administration only rated teams whose members also have an education only in business higher than other VCs. A strong bias also exists with respect to the type of firm where VC and members of the venture team have gathered prior professional experience. A rater who had been working exclusively in start-ups before joining the VC industry has a highly significant preference for teams whose members have prior experience mostly from start-ups. The same effect can be observed for VCs with prior experience obtained in large firms only; these individuals tend to prefer teams whose members have largely come from a large-firm background.

As any empirical study, our analysis and results come with some caveats. Due to our research design, we are limited to five dimensions of similarity. We find significant effects for stable and choice-based characteristics. It may well be that also other stable (e.g. sex, social and regional origins) or choice-based (e.g. university or other affiliations) characteristics have a likewise similarity effect. Future research on this issue is necessary.

One important alternative explanation of our results deserves a detailed comment. VCs might rate teams whose background is different from their own and thus unfamiliar to them on average correctly. However, they might be less proficient in assessing the team members' credentials in the respective field, and thus attain a lower accuracy in their rating. Given risk aversion, the rater might perform a risk-correction and downgrade the respective team. This effect would be even more pronounced if erroneous positive evaluations are considered more severe than erroneous negative evaluations by the VC. However, the latter assumption seems implausible given the early evaluation phase that we

consider. A false positive merely means that one team too many is invited for presentation. In fact, a false negative — excluding a team which in fact has a high potential — might actually constitute the bigger downside for the rater. Apart from that, in our experiment there were no credentials to assess. Finally – and most importantly – we find that VCs with both management and technical education still rate pure management teams as well as pure technical teams lower than heterogeneous teams. They do so despite the fact that they (the VCs) *are* familiar with these teams' respective background, such that a downward risk correction is not appropriate. Thus, the suggested alternative explanation of our findings does not appear convincing – they can indeed best be explained as similarity effects.

Our results have important implications for future research and for practitioners, for prospective entrepreneurs as well as their advisors and investors. As to academic research, most earlier studies of the VC evaluation process (with some notable exceptions discussed before) made the implicit assumption that VCs' ratings (of business plans, teams, etc.) are centered around a "correct" evaluation, deviating from it by random errors. Our results reject this assumption – deviations are not random, but contain systematic errors. These biases can be explained by including characteristics of the rater into the analysis. Future research into the VC evaluation process should take these results into account. Similarly, they are relevant for research into success factors of start-ups, as far as this includes assessments by VCs.

A rather interesting avenue for further research is to investigate similarity biases in later stages of the evaluation process. The present study finds significant biases even though the information describing the team was presented in a relatively objective manner, namely, in written form. Hence, we would expect even stronger distortions in later stages of the evaluation process, where personal interaction between rater and ratees plays a more prominent role. However, studying such effects will be challenging. Experimental designs become difficult to realize when face-to-face interaction is involved. On the other hand, real-world interactions – interviews, presentations – between VCs and venture teams are hard to observe, and even then they pose the problem of disentangling effects of team and business plan characteristics.

Venture capital firms should be somewhat worried about the similarity biases we identify. After all, what the "ideal team" for a new venture is should depend on the venture itself and maybe on some characteristics of the VC firm. The rater's personal profile, however, should only matter if this same person is likely to be the venture's coach in case the VC firm does grant financing. Under such circumstances it is possible – though by no means sure – that similarity simplifies interaction between the parties. A similarity bias would hence have some positive effects. In general, however, the initial rater will not be the team's future coach, such that the bias' negative effects come to bear. The influence of similarity biases on financing decisions is aggravated by the fact that, in our survey, in 55 percent of all cases plans are read by only one person before a decision to reject the proposal or to proceed with the evaluation is taken.

Hence, what can VC firms do to deal with the problem of biased evaluations? First of all, raters should try to get better insights into their individual decision processes (Zacharakis and Meyer, 1998; Shepherd, 1999), and should in particular find out if and to what degree they are prone to similarity biases. This may be done by systematic comparison and discussion of real team evaluations by different raters. Alternatively, VCs may employ an analysis as performed in this study, which could thus serve as a sort of decision aid for VCs similar to those suggested by Shepherd and Zacharakis (1999). Second, business plans (except those that are either good or bad beyond doubt) should be evaluated by more than one person, where it is clearly important that the readers' profiles are different. This leads to the third suggestion, namely, that VC firms should recruit their analysts in such a way as to achieve a healthy heterogeneity among their staff, in particular with respect to the type of education they have received and prior professional experience.

For new venture teams, our results imply that it may be important to find the right person within a VC firm who gets to read the business plan first. Thus, there are at least two practical implications for a start-up team seeking venture capital. First, while the common recommendation in the entrepreneurship literature states that start-up teams should attempt to submit their business plan via a person who is known to the VC, the majority of plans still is handed in on a "cold-call" basis. Thus, for those start-up teams that lack personal access to the VC of their choice, it seems to be a promising

strategy to conduct some prior research on the professionals in the VC firm who are involved in scanning business plans. Then they can try to submit their plan directly to the person whose profile fits best according to the criteria discussed in this paper. Though there are several evaluation criteria being used by VCs during the screening process, this strategy which focuses on the predominant evaluation criteria should to some extent improve the chances of getting past the first round of evaluations, where typically more than 80% of all new venture proposals are rejected (Roberts, 1991). Second, start-up teams should not be easily discouraged by a rejection, as it may be due to the fact that the team's and the rater's profiles were significantly different, and may not say too much about the team's and the venture's true qualities.

Predicting new firm performance is a very challenging undertaking. Given the sums that are at stake in the VC industry, the quality of an investor's evaluation process is crucial. Since, as MacMillan et al. (1985) point out, one should bet on the jockey, not the horse in order to identify emerging firms with high prospects for success, our analysis focuses on team characteristics – the most important dimension of a new venture. By pointing out flaws in the standard process, this study should hopefully be a useful contribution to improving theory and the evaluation process of venture capitalists.

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Figure 1
Questionnaire for participating VCs

- *What kind of education did you receive? (several answers possible)*

    Apprenticeship   University degree   Ph.D.   Master

- *What is your field of education? (several answers possible)*

    Business/economics   Technical   Science   Law   Other: _____

- *What is your age?* ____ years

- *For how many years have you been working as a VC investor?* ____ years

- *For how long have you been working with your current employer?* ____ years

- *Do you have professional experience from fields outside VC? If so, …*

    a) *… in companies of what size? (several answers possible)*

        Start-up   SME   large firms   no professional experience in other firms

    b) *… did you have, as a manager, responsibility for staff?*

        no   1-5 staff   6-20 staff   > 20 staff

- *How important do you consider product idea, market, and venture team in your investment decisions? Please attribute a total of 12 points to these features, according to their importance.*

    product idea   ____ points

    market   ____ points

    venture team   ____ points

Figure 2
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

Table 1
Attributes and realizations of VC characteristics
pertaining to similarity effects

age of VC	30 yrs and younger N=8	between 30 and 40 years old N=34	40 yrs and older N=9
level of education of VC	apprenticeship N=4	doctoral degree N=11	any degree , but no apprenticeship and no doctoral degree N=36

field of education of VC	engineering or science only N=11	business administration only N=25	engineering/ science & business administration N=12	other N=3
prior job experience of VC	start-up only N=2	large firm only N=15	start-up and large firm N=16	other type of firm N=18
prior VC experience in leading teams	none N=9	for 1-5 employees N=20	for 6-20 employees N=16	for more than 20 employees N=6

Table 2
Attributes and realizations
of team characteristics as used on conjoint cards

Variable	Realization 1	Realization 2	Realization 3
age of team members	25-35 years (N=6)	35-45 years (N=6)	25-45 years (N=8)
level of education: unversity degree	none of the team members (N=6)	some team members (N=7)	all team members (N=7)
field of education	all management (N=9)	some management, some engineering (N=5)	all engineering (N=6)
prior job experience: type of firm	mostly large firms (N=9)	some large firms, some start-up (N=5)	mostly start-up (N=6)
relevant industry experience	no one (N=7)	some (N=7)	all (N=6)
experience in leading teams (5 to 10 people)	no one (N=6)	some (N=7)	all (N=7)
acquaintance among team members	brief (N=7)	for a longer time, privately (N=7)	for a longer time, professionally (N=6)

Table 3
Percentage of top quartile observations
by team characteristics

Variable	preferred realization	second-best realization	third-best realization
age of team members	**37.3%** **35-45 years**	21.3% 25-45 years	*17.6%* *25-35 years*
level of education: unversity degree	**33.1%** **all team members**	29.4% some team members	*10.5%* *none of the team members*
field of education	**38.8%** **some management, some engineering**	23.5% all engineering	*15.7%* *all management*
prior job experience: type of firm	**30.2%** **some large firms, some start-up**	25.5% mostly start-up	*21.8%* *mostly large firms*
relevant industry experience	**43.1%** **all**	31.7% some	*2.8%* *no one*
experience in leading teams (5 to 10 people)	**33.3%** **all**	27.7% some	*12.1%* *no one*
acquaintance among team members	**32.7%** **for a longer time, professionally**	23.0% for a longer time, privately	*20.4%* *brief*

Table 4
Ordered Probit Estimation Results on Rank Quartiles

Independent Variable	(1) Coefficient (S.E.)	(2) Coefficient (S.E.)	(3) Coefficient (S.E.)	(4) Marginal Effects
All team members between 25 and 35 years old	-0.497***	-0.460***	-0.500***	-0.113
	(0.088)	(0.097)	(0.089)	
All team members between 25 and 45 years old	-0.372***	-0.346***	-0.373***	-0.086
	(0.095)	(0.089)	(0.096)	
No team member with academic education	-0.977***	-0.988***	-0.982***	-0.205
	(0.086)	(0.075)	(0.086)	
Some team members with academic education	-0.176**	-0.174***	-0.173**	-0.044
	(0.074)	(0.061)	(0.075)	
All team members with business administration training only	-1.064***	-1.116***	-1.107***	-0.245
	(0.091)	(0.099)	(0.099)	
All team members with technical training only	-0.810***	-0.714***	-0.723***	-0.169
	(0.075)	(0.066)	(0.067)	
Team members' prior job experience mostly in large firms	-0.134*	-0.162	-0,166	-0.035
	(0.089)	(0.119)	(0.112)	
Team members' prior job experience mostly in start-ups	-0.158**	-0.145*	-0.149**	-0.032
	(0.073)	(0.074)	(0.073)	
No team member with prior experience in the relevant industry	-1.810**	-1.825***	-1.824***	-0.375
	(0.090)	(0.090)	(0.091)	
Some team members with prior experience in the relevant industry	-0.351***	-0.353***	-0.353***	-0.108
	(0.078)	(0.078)	(0.077)	
No team member with prior experience in leading teams	-0.802***	-0.763***	-0.809***	-0.171
	(0.049)	(0.067)	(0.049)	
Some team members with prior experience in leading teams	-0.164**	-0.140*	-0.168**	-0.041
	(0.070)	(0.077)	(0.070)	
Team members acquainted privately for some time	-0.359***	-0.362***	-0.362***	-0.078
	(0.070)	(0.070)	(0.069)	
Team members acquainted only briefly	-0.616***	-0.622***	-0.621***	-0.126
	(0.063)	(0.064)	(0.063)	

VC 40 yrs and older - team members between 35 and 45 years old	0.164		
	(0.190)		
VC 30 yrs and younger - team members between 25 and 35 years old	-0.061		
	(0.229)		
VC with apprenticeship training - no team member with academic education	0.075		
	(0.172)		
VC with doctorate degree - all team members with academic education	-0.007		
	(0.177)		
VC and team with technical training only	-0.105	-0.069	-0.014
	(0.121)	(0.117)	
VC and team with management training only	0.254**	0.235**	0.050
	(0.104)	(0.106)	
Team and VC with management and technical training	0.350**	0.343**	0.075
	(0.175)	(0.169)	
VC and team with experience mostly in start-ups	0.319*	0.331**	0.073
	(0.186)	(0.168)	
VC and team with experience mostly in large firms	0.174	0.174*	0.037
	(0.117)	(0.104)	
VC and team with experience in start-ups and large firms	0.083**	0.071**	0.015
	(0.034)	(0.026)	
VC and team with strong experience in leading teams	0.059		
	(0.076)		
VC and team with weak experience in leading teams	-0.104		
	(0.191)		
Cutoff value 1	-3.871 (0.188)	-3.740 (0.176)	-3.796 (0.193)
Cutoff value 2	-2.887 (0.169)	-2.750 (0.158)	-2.806 (0.174)
Cutoff value 3	-1.854 (0.143)	-1.707 (0.129)	-1.765 (0.147)
Test 1: all team characteristics - p-value (df)	p<0.001 (14)	p<0.001 (14)	p<0.001 (14)
Test 2: all similarity variables - p-value (df)	-	p<0.001 (12)	-
Test 3: similarity in age, type of education, leading teams - p-value (df)	-	p=0.183 (6)	-
Test 4: similarity in firm type experience, discipline of training - p-value (df)	-	p<0.001 (6)	p<0.001 (6)
Observations	1020	1020	1020
log L	-1093.59	-1087.25	-1088.20
Pseudo R2	0.2266	0.2313	0.2304
Chi-squared	2170.7	1325.4	826.7
degrees of freedom	14	26	20

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix: Demographics of surveyed VC firms and individuals

<u>VC firms (N = 26)</u>

Age (years):	mean = 8.2, standard dev. = 12.6, median = 3, range: 1-56
Size (number of professionals):	mean = 75.4, standard dev. = 202.8, median = 9, range: 1-800
Funds volume (EURO):[*]	<10 mio.: 2; 26-100 mio.: 8; 101-250 mio.: 5; >250 mio.: 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-/m-commerce: 19;
	electrical engineering: 13; biotechnology: 10; services: 5; other: 13
Location of interviews (offices):[*]	Munich: 40; Vienna: 7; Berlin: 4

<u>Individuals (N = 51)</u>

Age:	mean = 35.0, standard dev. = 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, standard dev. = 5.2, median = 2, range: 0-30
Tenure with firm (years):	mean = 2.4, standard dev. = 2.0, median = 2, range: 0-11
Number of business plans evaluated:	mean = 460, standard dev. = 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
Personnel responsibility[*]	none: 9; 1-5 subordinates: 20; 6-20 subordinates: 16; >20 subordinates: 6

[*] For categorial variables, the number of respondents who chose the respective category is given. [**] Multiple answers possible.