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DISENTANGLING THE EFFECTS OF NEW VENTURE TEAM FUNCTIONAL HETEROGENEITY ON NEW VENTURE PERFORMANCE^{*}

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Abstract: Previous research on entrepreneurial teams has failed to settle the controversy over whether team heterogeneity helps or hinders new venture performance. Reconciling this inconsistency, this paper suggests a new conceptual approach to disentangle differential effects of team heterogeneity by modeling two separate heterogeneity dimensions, namely knowledge scope and knowledge disparity. Analyzing unique data on functional experiences of the members of 337 start-up teams, we find support for our contention of team heterogeneity as a two-dimensional concept. Results suggest that knowledge disparity negatively relates to both start-ups’ entrepreneurial and innovative performance. In contrast, we find knowledge scope to positively affect entrepreneurial performance, while it shows an inverse U-shaped relationship to innovative start-up performance.

Keywords: Entrepreneurial teams · New venture performance · Team heterogeneity · Team diversity

JEL classification: L26 · M13 · L25

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1. Introduction

It is widely acknowledged that entrepreneurship occurs as a shared effort with new firms more often being created by groups of people than by individuals (Davidsson & Wiklund, 2001; Francis & Sandberg, 2000; Gartner et al., 1994; Kamm et al., 1990; Roberts, 1991). Entrepreneurial teams have recently been identified as an “omnipresent phenomenon” describing “the superior entrepreneurial start-up concept” (Lechler, 2001, p. 264). An emerging, though relatively limited, body of entrepreneurship literature has given ample empirical support to the notion that team start-ups indeed perform better than solo ventures (e.g., Chandler et al., 2005; Chowdhury, 2005; Ucbasaran et al., 2003). Accordingly, the apparent success of entrepreneurial teams can be attributed to the logic that particularly “high technology industries might require more skills than an individual would be likely to have, necessitating that individuals combine their abilities in teams in order to start an organization successfully” (Gartner 1985, p. 703).

One of the most discussed team issues deals with the composition of successful teams, especially with regard to heterogeneity and homogeneity. In particular, the upper echelon theory (Hambrick & Mason, 1984) posits that characteristics of the members of top management teams drive venture performance. While most of this research has been conducted by analyzing the impact of top management team heterogeneity on the performance of established companies, studies in the context of entrepreneurial teams are scarce (for notable exceptions see, e.g., Chowdhury, 2005; Liao et al., 2009). We attempt to fill this gap in the literature and provide empirical evidence regarding one specific characteristic of entrepreneurial teams that has been identified as a centrally important determinant of venture performance (Hambrick & Mason, 1984) – team members’ functional experiences. A focus on functional experience heterogeneity acknowledges that individual team members carry their prior experiences across organizational settings. In our case, functional background therefore provides one useful and accessible indicator of the experiential resources housed within the start-up team.

Previous research examining the performance benefits of functional heterogeneity in teams has been decidedly equivocal, reporting positive relationships in some cases and negative or null relationships in others (e.g., Bantel & Jackson, 1989; Chowdhury, 2005; Hambrick, Cho, & Chen, 1996). It is our contention that this conflicting pattern of empirical evidence can be attributed to limitations in the theoretical and empirical assessment of functional team heterogeneity. Studies on team composition typically employ a unidimensional approach and rely on heterogeneity indices that tend to capture a net effect (see, e.g., Amason et al., 2006; Eisenhardt & Schoonhoven, 1990), not taking account of potentially countervailing influences of functional team heterogeneity on team performance. Recent studies provide some support for this argument. Reviewing the literature on functional team heterogeneity, Bunderson and Sutcliffe (2002) and Bunderson (2005) reveal different conceptualizations of functional heterogeneity yielding different implications for team outcomes. In their study on 45 top management teams from a Fortune 100 consumer products company, Bunderson and Sutcliffe (2002) also find empirical support for their conjecture of a positive and negative impact of functional heterogeneity on team processes and performance. Liao et al. (2009) further differentiate between a functional and a social view on founding teams’ heterogeneity. Investigating the probability of setting up a new venture in a sample of nascent start-up teams, their results suggest that both theoretical perspectives differently affect the venture creation process.

The present paper builds on these studies, but introduces a new conceptual approach to disentangle differential effects of functional team heterogeneity of start-up teams on subsequent new venture performance. Drawing on two established schools of thought, the cognitive resource perspective (Cox

& Blake, 1991; Hambrick & Mason, 1984; Wiersema & Bantel, 1992) and similarity/attraction theories (Byrne, 1971; Hogg & Abrams, 1988; Tajfel & Turner, 1986), we model two separate heterogeneity dimensions. Related to the former perspective, the *knowledge scope* dimension captures the beneficial effects of functional team heterogeneity ascribed to the breadth of a team's cognitive resources. The *knowledge disparity* dimension relates to similarity/attraction theories. It captures the detrimental effects of functional team heterogeneity ascribed to social categorization processes.

Given this theoretical foundation, we first aim to empirically separate the two heterogeneity dimensions *knowledge scope* and *knowledge disparity*. We then investigate the effects that both heterogeneity dimensions have on a team start-up's entrepreneurial performance (measured in terms of firm survival and employment growth) and innovative performance (measured in terms of the number of patent applications). Empirical estimations employing the traditional unidimensional approach further allow us to compare our newly-developed conceptualization of team heterogeneity with the conceptualization established in the team literature. For our empirical analyses, we employ a unique dataset consisting of 337 team start-ups established between 1994 and 2006 in innovative industries in the German federal state of Thuringia. More specifically, we use information on the functional background experiences of each team member to develop new measures of start-up team heterogeneity.

The remainder of the paper is organized as follows. In the next section, our conceptual model of new venture team heterogeneity and related hypotheses are set out. Section 3 is dedicated to the presentation of our data and the variables used. The empirical analysis is presented in Section 4. Section 5 discusses our findings, provides implications for theory and practice, and points out limitations of the present study. Finally, Section 6 concludes.

2. Conceptual Background

2.1 Theoretical Perspectives on the Heterogeneity-Performance Link

Research in organizational demography and small group behavior provides two competing schools of thought that have been advanced in order to explain performance effects of team composition. On one side, the cognitive resource perspective argues for a positive effect of team heterogeneity on team performance (Hambrick & Mason, 1984; Wiersema & Bantel, 1992). Specifically, it is suggested that a team's composition is an indicator of its cognitive resources, that is, pooled sets of contacts, skills, information, and expertise available for the team to draw on. As stated by Milliken and Martins (1996, p. 404), "a group that is diverse could be expected to have members who may have had significantly different experiences and, therefore, significantly different perspectives on key issues or problems." Accordingly, as team heterogeneity increases, so do the team's cognitive resources. The wider breadth of cognitive perspectives and abilities is assumed to enhance information processing and encourage teams to be more effective solving complex, non-routine problems (Ancona & Caldwell, 1992; Bantel & Jackson, 1989; DeDreu & West, 2001; Hambrick et al., 1996).

On the other side, similarity/attraction theories propose that heterogeneity is detrimental to team performance (Byrne, 1971). Following this perspective, team members prefer to interact with and regard as attractive those individuals whom they perceive as similar to themselves. Team member heterogeneity on any attribute, thus, can decrease interpersonal liking, impede effective communication, and undermine team cohesiveness. Social identity theory and social categorization

theory (Hogg & Abrams, 1988; Tajfel & Turner, 1986) make similar predictions about a heterogeneous team's functioning. These theories hold that, based on perceptions of similarities and differences, individuals subconsciously group themselves and others into social categories (defined, e.g., in terms of age, gender, tenure, function) when making judgments or decisions. Categorization and social comparison, in turn, lead to favoring similar team members (their in-group), while distancing from dissimilar team members (the out-groups). These in-group/out-group biases (e.g., incumbent team members vs. "newcomers"; accountants vs. engineers) tend to give rise to negative team interaction patterns such as less commitment and more detrimental conflict and factionalism (Jehn et al., 1999; Pelled et al., 1999; Williams & O'Reilly, 1998).

In summary, heterogeneity may provide benefits for team performance, while it also involves the risk of incurring process losses (that may partly offset these advantages). This has been coined the "double-edged sword" of team heterogeneity (Milliken & Martins 1996), illustrating the lack of consensus on how team composition influences team outcomes.

In order to reconcile the controversy over whether team heterogeneity helps or hinders new venture performance, we build on recent theoretical and operational developments in the fields of top management team and entrepreneurial team research (Bunderson, 2005; Bunderson & Sutcliffe, 2002; Liao et al., 2009). In particular, we propose a two-dimensional approach to capture differential effects of new venture team heterogeneity. Focusing on the functional experience of each team member at the time of venture creation, this approach allows to model two separate heterogeneity dimensions which both affect subsequent team performance differently. Drawing from the cognitive resource perspective, the first dimension, *knowledge scope*, is defined as the breadth of a new venture team's knowledge stock. The second dimension, *knowledge disparity*, relates to similarity/attraction theories. It is defined as the deviation in the knowledge stocks of the individual team members.

2.2 Hypotheses

2.2.1 Knowledge Scope and Entrepreneurial Firm Performance

From a cognitive resource perspective, heterogeneity in team members' functional experience is likely to have a positive impact on new venture performance as it provides a diverse stock of knowledge, capabilities, and expertise upon which the team can draw on when pursuing entrepreneurial activities (Milliken & Martins, 1996; Randel & Jaussi, 2003). Consistent with this notion, Roure and Maidique (1986) report that an entrepreneurial team's "completeness" – the degree to which key positions (e.g., marketing, engineering, finance) are staffed by experienced team members – is positively associated with survival and growth of the new firm. Ensley and Hmieleski (2005) find a positive relationship between an entrepreneurial team's functional heterogeneity and net cash flow and sales growth of the new venture. Furthermore, there is some evidence that start-up teams' functional experience shapes the competitive strategies, and ultimately performance, of new ventures (Boeker, 1989; Shane & Stuart, 2002; Shrader & Siegel, 2007). For example, a broad scope of functional experiences has been found to improve organizational responsiveness to competitors' actions (Hambrick et al., 1996) and to environmental shifts, caused, e.g., by technological discontinuities (Keck & Tushman, 1993). According to Hambrick et al. (1996, p. 665), the heterogeneous team has a broader potential behavioral repertoire and is able to "conceive and launch actions on many fronts." This is in line with research in the managerial cognition tradition, which let us believe that what external information the

start-up team attends to and incorporates into strategic decision making is influenced by team members' expertise and prior knowledge (Cho & Hambrick, 2006; Ocasio, 1997).

Differing viewpoints, expertise, and opinions may also be the cause of disagreement about team tasks, producing cognitive or task-related conflict among team members (Jehn et al., 1999; Jehn, 1995; Pelled et al., 1999). Presumably, task-related conflict can be beneficial to new firm performance, for it is through their attempts to resolve such conflict that entrepreneurial team members are likely to find creative and effective solutions (Amason & Sapienza, 1997; Jehn 1995). Researchers suggest that task conflict promotes open and deliberate debate on ideas, which encourages greater cognitive understanding of the task issues at hand and culminates in improved team decisions (Amason, 1996; Ensley & Pearce, 2001; Ensley et al., 2002; Simons & Peterson, 2000).

Apart from intra-team processes, the scope of functional heterogeneity may also provide a signal to external stakeholders and investors about the new venture's growth prospects (Beckman et al., 2007). Foo et al. (2005), in a study on nascent start-up teams, reveal beneficial effects of team heterogeneity when presenting the business idea to external evaluators. Likewise, Zimmermann (2008) shows that higher levels of functional heterogeneity among team members enable firms to raise more capital at their initial public offering. She concludes that investors positively value breadth in the functional backgrounds as it may signal that the management team has the talent to make the firm profitable and therefore a worthwhile investment.

Consequently, a heterogeneous start-up team in terms of a broader knowledge base should be more capable of identifying a viable business opportunity, building a resource base, and setting up and maintaining entrepreneurial activities. The corresponding hypothesis is formulated as follows:

H1a: A start-up team's knowledge scope is positively related to the new firm's entrepreneurial performance.

2.2.2 Knowledge Disparity and Entrepreneurial Firm Performance

Beside the advantages associated with heterogeneous functional experience stemming from knowledge scope, disparity in the functional background of start-up team members may negatively impact team performance. Consistent with similarity/attraction theories, potential problems of functionally heterogeneous teams have mainly been attributed to substantive disagreements among team members centering on differences in professional vocabularies, cognitive patterns, and styles (Drach-Zahavy & Somech, 2001; Lovelace et al., 2001). These problems might be particularly evident in innovative team start-ups that attempt to create and market entirely new products or services. As Amason et al. (2006) note, managing such novel environments requires team members to communicate frequently and share information through informal, face-to-face interaction. In a similar vein, Ensley et al. (1998) explain that the dynamic and uncertain nature of an entrepreneurial endeavor places a premium on smooth interaction and team effectiveness. Chatman and Flynn (2001) suggest that the more uncertain the environment the more prone people are to socialize with others that are similar. Related to these arguments is Mathieu et al.'s (2000) notion that team members must share similar mental models in order to anticipate each other's actions and to coordinate their behaviors, especially when time and circumstances do not permit overt and lengthy communication and strategizing. Mental models "help people to describe, explain, and predict events in their environment" (Mathieu et al., 2000, p. 274). While the sharing of mental models enables team members to be "on the same page" during task

execution and benefits team performance (Mathieu et al., 2000), differences can become a barrier for effective communication and understanding (Amason, 1996). Hence, start-up teams with disparate functional backgrounds may find it difficult to develop a shared understanding of team tasks, like the marketing of their highly novel product, because of team members' divergent definitions of even basic terms such as "product" and "market" (Ancona & Caldwell, 1992).

Divergent perceptions on how the start-up team should operate in order to realize its goals further increase the likelihood that misunderstanding and misinterpretation triggers affective disputes among team members (Ancona & Caldwell, 1992; Eisenhardt et al. 1997; Ensley et al., 2002). Affective or relationship conflict derives from personal dislikes and animosities and can represent many aspects of dysfunctional interpersonal relationships, including suspicion and hostility (Amason & Sapienza, 1997; Jehn, 1995). In contrast to the previously mentioned task-related conflict, relationship conflict is considered detrimental to team performance (DeDreu & Weingart, 2003; Pelled et al., 1999). It limits the team's information processing ability because team members spend their time and energy focusing on each other rather than on task-related issues (Simons & Peterson, 2000).

To conclude, functional background heterogeneity in terms of divergences in team members' knowledge stocks has a negative effect on team performance by negatively impacting social interactions and cohesion between members of the start-up team. Hence, we expect:

H1b: A start-up team's knowledge disparity is negatively related to the new firm's entrepreneurial performance.

2.2.3 Knowledge Scope and Innovative Firm Performance

Functional heterogeneity also can be considered an important driver of innovation and creativity in organizations (Bantel & Jackson, 1989; Drach-Zahavy & Somech, 2001; Hambrick et al., 1996). Again in line with the cognitive resource perspective, a broad set of functional experience provides the team with unique information and perspectives, which may stimulate innovative team performance (Ancona & Caldwell, 1992; DeDreu & West, 2001). In related research, Cohen and Levinthal (1990) contend that a firm's ability to access and exploit new knowledge, which they label absorptive capacity, should be greater the more diverse the knowledge stocks held by individuals in the firm are. Heterogeneity in this respect facilitates organizational learning and the identification of new resource combinations that offer the potential for entrepreneurial profits (Hayton & Zahra, 2005). Moreover, by opening up constructive discussion (DeDreu & West, 2001) and encouraging "out-of-the-box" thinking (Lovelace et al., 2001), cognitive conflict appears to promote innovative team performance. Thus, all else being equal, start-up teams with functional experience in different fields should be more capable of turning creative ideas and individually-held knowledge into new products, processes, and services.

There is some empirical evidence that supports this line of reasoning. For example, Bantel and Jackson (1989) observe, in a sample of managerial teams in the finance sector, that heterogeneity in relation to the functional area from which managers came was positively associated with the number of innovations adapted or developed by the firms. Ancona and Caldwell (1992) find that members of cross-functional product development teams communicated more frequently outside their teams, which led to more creative ideas. Smith et al. (2005) demonstrate that the rate of new product and service introductions in high-technology firms was a function of the firms' knowledge creation

capabilities as measured by the scope of functional experiences in managers' and employees' knowledge stocks.

However, exposure to multiple functional perspectives may not per se help produce innovative output. At some point, the benefits of an increased knowledge base are expected to be offset by the team's difficulties in information processing (Cho & Hambrick, 2006; Milliken & Martins, 1996; Ocasio, 1997; Sethi et al., 2001). Accordingly, at the highest levels of a start-up team's functional background heterogeneity – i.e., the case of teams made up of individuals with entirely different professional histories – it is most likely that team members will not share a common frame of reference that would allow for the comprehension of others' divergent expertise and knowledge (van Knippenberg & Schippers, 2007). The lack of a common frame of reference to build on may impede interpersonal communication and information sharing, with innovative team performance suffering (Bunderson & Sutcliff, 2002; Nahapiet & Goshal, 1998; Van der Vegt & Bunderson, 2005). Conversely, at the lowest levels of a team's functional background heterogeneity, team members may share largely similar and redundant knowledge bases. Therefore, start-up teams low on heterogeneous functional experience are less likely to possess distinct perspectives that may eventually lead to more innovative output (DeDreu & West, 2001).

Taking the aforementioned arguments together, we suggest an inverse U-shaped relationship between the scope of the knowledge base of start-up teams and the innovative performance of the new firm. As knowledge scope increases from a low to a moderate level, the start-up's innovative performance increases. Beyond a moderate level, the scope of represented functional experience in the team has a negative effect on innovative performance. Thus, the following hypothesis applies:

H2a: *Innovative performance of the new firm is highest at a moderate level of the start-up team's knowledge scope.*

2.2.4 Knowledge Disparity and Innovative Firm Performance

In contrast, the social similarity and attraction approaches would suggest that heterogeneous start-up teams may generally be ineffective at capitalizing on divergent knowledge and expertise with regard to innovation. Accordingly, increasing diversity in team members' functional backgrounds can induce social categorization processes and in-group/out-group biasing (Van der Vegt & Bunderson, 2005; Williams & O'Reilly, 1998). The flipside of a positive bias toward one's own functional category is stereotyping and discrimination of team members with different functional backgrounds (Tajfel & Turner, 1986). For example, in a recent meta-analytic review, Mesmer-Magnus and DeChurch (2009) reveal that teams are more likely to share information when team members are highly similar to one another with respect to training and background characteristics. In the same line, Van Knippenberg et al. (1994) report that information was given more attention, seen as more accurate, and deemed as more trustworthy when provided by in-group team members, irrespective of the objective quality of the information. In fact, in functionally heterogeneous start-up teams the tendency may be to stereotype out-group members by assuming that they "just don't understand" and argue and defend rather than seek integration of different perspectives and ideas. Categorization of team members into those belonging to a functional in-group and out-group may, thus, create a barrier to cooperative behavior and may even stimulate competitive behavior among members of the same team (Brewer, 1995). Maltz and Kohli (1996) report that perceived inter-functional rivalry (i.e., rivalry between marketing and non-marketing functions) reduce the willingness to provide, and to be receptive to

knowledge exchange across functional boundaries while contact between cross-functional team members was restricted to formal meetings.

Thus, in functionally heterogeneous teams cooperation problems, distrust, and stereotyping may compromise team members' motivation to share knowledge and information. Existing research suggests however that information sharing is a crucial mechanism for translating functional heterogeneity into innovative team performance (Bantel & Jackson, 1989; Drach-Zahavy & Somech, 2001). Drach-Zahavy and Somech (2001) find that team members must exchange information, learn, negotiate, and motivate each other in order to make proper use of their divergent functional experience, and work effectively and innovatively.

In sum, due to processes associated with social categorization, divergences in team members' knowledge stocks may become a liability diminishing team innovation. We therefore expect:

H2b: *A start-up team's knowledge disparity is negatively related to the new firm's innovative performance.*

3. Methods

3.1 Sample and Data Collection

The data for our analysis are provided by the Thuringian Founder Study (*Thüringer Gründer Studie*), an interdisciplinary research project on success and failure of innovative start-ups in the German federal state of Thuringia.¹ This dataset draws from the German trade register (*Handelsregister*) for commercial and private companies established in Thuringia between the years 1994 and 2006. It is further restricted to start-ups in innovative industries, comprising 'advanced technology' and 'technology-oriented services' according to ZEW classification (Grupp et al., 2000)². The survey population consists of 4215 founders who registered 2971 new entries in the *Handelsregister*.

From this survey population, a random sub-sample of 3671 founders was drawn and contacted. Due to team-started ventures, this corresponds to 2604 start-ups in innovative industries. From January to October 2008, we conducted 639 structured face-to-face interviews with either the solo entrepreneur or with the lead entrepreneur of team start-ups, resulting in a response rate of about 25%. There is no response bias with regard to industry structure and gender of founders.³

¹ For the benefit of the reader, we provide some background information about Thuringia. As part of the former GDR, Thuringia (population of about 2.3 million people, gross national product of about 72% of the German average in 2007) has undergone the post-communist transformation process from a planned to a market economy. Comparing Thuringia's industry structure in terms of employment shares with the German average, the public sector still plays an important role, while manufacturing industries and the private service sector remain slightly underrepresented. Looking more closely at the entrepreneurial activity in innovative industry sectors, Thuringia has comparatively more start-ups in optics and fine mechanics and less in services than the other German federal states.

² Grupp et al. (2000) define innovativeness at the industry level according to the average investments in R&D activities. Thereafter, innovative industries are characterized by firms' average R&D expenditures of at least 3.5% of their turnover.

³ Since the German trade register only provides limited ex-ante information about registered start-ups we had to stick to these characteristics in order to test for the representativity of our sample.

The structured interviews were carried out by the members of the research project. On average, an interview took approximately one and a half hours. The interviews covered a broad set of questions regarding socio-demographic and psychological data of the founders. Retrospective data were collected relating to events in the founder's life and the business history, covering the venture creation process and the first three business years of the start-up⁴. To overcome entrepreneurs' hindsight bias and memory decay (Davidsson, 2006), we utilized mnemonic techniques drawn from the Life History Calendar method (Caspi et al., 1996).⁵ This method has been shown to collect more valid and reliable retrospective information than traditional questionnaires (Belli et al., 2001; 2004). The focus on firms in a single region (the German federal state of Thuringia) further allows us to hold constant key labor market and environmental conditions. Another important advantage of our study design is the possibility to interview founders of companies which had failed at the time of data collection. Hence, our sample is not biased toward surviving or successful firms.

Since we choose the start-up team as the unit of analysis, we only rely on data regarding the 410 team-started companies in our database. Thereby, a start-up team is defined as two or more persons who have been actively involved in the venture creation process and own or have owned a part of the new venture (Gartner et al., 1994; Kamm et al., 1990).⁶ Due to the fact that some of these start-ups were not genuinely new but subsidiaries or diversifications of existing companies, we had to omit 53 observations. Furthermore, we had to exclude 20 observations from the analysis due to incomplete data. Our final sample consists of 337 start-up teams.

3.2 Dependent Variables

3.2.1 Entrepreneurial Performance

We use two indicators to gauge team start-ups' entrepreneurial performance: venture survival and employment growth. First, we consider *venture survival* because it is among the most commonly used dependent variables in entrepreneurship research and can be seen as the minimum criterion for entrepreneurial success (Brüderl & Preisendörfer, 1998). In the present study, this variable indicates whether a team-started new venture survived a minimum of three years after start-up, measured dichotomously (1 = survived at least the first three business years; 0 = closed before year three). Second, *employment growth* is approximated by the new firms' absolute number of employees in the third business year. Members of the new venture team as well as the board of directors (where applicable) are not counted as employees. Growth in employment is used as performance indicator because it signals the need for additional resources to meet customer demands. Relative growth rates could not have been computed as our sample consists of genuinely new firms which in most cases

⁴ We define the first business year as the time when accounting started either because of obligations from the German trade register or because of first revenues. Thus, this definition does not necessarily correspond to the date of registration at the *Handelsregister*.

⁵ We employ a study-specific version of the Life History Calendar, which is a data-collection tool established in sociological and psychological research. It is based on the principles of the autobiographic memory. This means that, in a first step, we asked interviewees about the timing of well-known life events, sequences, and transitions (e.g., marriage, birth of children, education, or professional life). In a second step, these events served as anchors for the recall of our retrospective study variables.

⁶ Persons entering to and exiting from the team were also counted as team members.

started with zero employment (for a similar approach see Baum et al. (2001)). If a new venture did not reach its third business year we recoded the number of employees as zero.

As Sapienza et al. (1988, p. 46) observe, “many owners/entrepreneurs for a variety of reasons report manipulated performance outcomes.” Therefore, we gathered objective information regarding the number of employees in the third business year from two business information providers (*Creditreform* and *Bureau van Dijk*). Secondary data and data from our survey overlapped for 66 team start-ups, giving us the opportunity to validate the employment growth measure used in this study. Correlations between both data sources indicate validity of our measure of firm growth ($r = .78, p < .001$).

3.2.2 Innovative Performance

To measure team start-ups’ innovative performance, we count the *number of patent applications* which either members of the founding team (as inventor) or the company (as applicant) filed during the first four years of business operation. Therefore, data on patent applications at the German Patent Office (*DPMA*) were accessed.⁷ We focus on patent output because patents are tangible manifestations of firms’ ideas, techniques, and products (DeCarolis & Deeds, 1999), and represent an important milestone in the innovation process within firms. Furthermore, patenting performance has frequently been used to measure innovative firm behavior in past research (Ahuja & Katila, 2001; Griliches, 1990; Hall and Ziedonis, 2001).⁸

3.3 Independent Variables

Even though functional heterogeneity in teams has been conceptualized in a number of different ways (for a review see Bunderson & Sutcliff, 2002), they typically take account of the distribution of team members’ prior experiences across different functional categories. The most commonly employed measure of a team’s functional heterogeneity is Blau’s (1977) index (see Harrison & Klein, 2007) $1 - (\sum_{i=1}^n p_i^2)$, where p_i denotes the proportion of team members with prior experience in the i th functional category. However, this measurement approach does not allow the consideration of two separate dimensions of functional heterogeneity. Instead, Blau’s (1977) index captures an overall net effect of the productive and destructive impact team heterogeneity has on team performance (see discussion in Section 2.1).

⁷ Applying for a patent at the *DPMA* involves lower fees as compared to applications at, e.g., the European Patent Office (*EPO*). This implies that smaller firms, not being able or willing to bear the higher fees, will apply at the *DPMA* alone. However, applications at the *EPO* that cover the German territory will appear in the *DPMA* dataset as well. We therefore can expect the German database to be more complete.

⁸ There are several potential shortcomings of patent applications as a measure of innovative firm performance that should be kept in mind (see Griliches, 1990, for an extended discussion of this topic). Most importantly, patent data might underestimate innovative activity because firms might use other strategies to protect the output of R&D efforts, for example secrecy or speed of innovation (Mansfield et al., 1991; Cohen et al., 2000). Firms might not patent because not all inventions are patentable, such as inventions in the service sector. Other reasons for not patenting might include the lengthy application process relative to the duration of the innovation cycle or the ease of inventing around (Cohen et al., 2000).

In order to more adequately capture a start-up team's functional heterogeneity, we aim to disentangle functional heterogeneity into two separate dimensions, namely *knowledge scope* and *knowledge disparity*. On that account we apply four different heterogeneity indices. More precisely, *variety* and *diversity* indices are used to build the measure of knowledge scope, capturing the breadth of the teams' knowledge base. *Dissimilarity* and *non-redundancy* indices form the knowledge disparity measure, which capture divergences within the structure of the functional background among the team members.

In our paper, the calculation of the four different heterogeneity indices draws from the functional background experiences that start-up team members have acquired prior to the first steps in the venture creation process. To gather this information, interviewees were asked to indicate whether each member of their start-up team possessed prior work experience in each of six functional categories: management, marketing or sales or promotion, accounting or controlling or financing, engineering or R&D, production, and personnel. These functional categories have frequently been used in previous studies on venture team heterogeneity (e.g., Murray, 1989; Zimmerman, 2008). For reasons of time constraints, data on functional experience were collected for a maximum of five team members. In the following sections, we demonstrate how the indices of *variety*, *diversity*, *dissimilarity*, and *non-redundancy* were calculated in order to finally obtain our measures of knowledge scope and knowledge disparity. An example clarifying the underlying calculations is provided in the Appendix.

3.3.1 Knowledge Scope

Both *variety* and *diversity* are captured with an entropy-based indicator of team heterogeneity. Originally developed by Shannon (1948) in the communication literature, we apply the formalization Hill (1973) and Baumgärtner (2004) adapted to study ecological and product heterogeneity, respectively. Following their lead, entropy is defined as

$$v_a(s) = \begin{cases} (\sum_{i=1}^n s_i^a)^{1/(1-a)}; & a \geq 0, a \neq 1 \\ \lim_{a \rightarrow 1} (\sum_{i=1}^n s_i^a)^{1/(1-a)}; & a = 1. \end{cases} \quad (1)$$

As a central parameter, s_i denotes the weighted probability that members of the start-up team are experienced in the functional category i . Therefore, the number of team members' experiences in the functional category i is weighted against the total number of experiences the start-up team possesses in all functional categories. Put formally,

$$s_i = \sum_{j=1}^m x_{ij} / \sum_{i=1}^n \sum_{j=1}^m x_{ij}, \quad (2)$$

where n denotes the total number of functional categories in which each team member might have gained practical experience prior to start-up, m denotes the total number of team members, and x_{ij} is defined by

$$x_{ij} = \begin{cases} 1 & \text{if team member } j \text{ has experience in the functional category } i \\ 0 & \text{otherwise.} \end{cases}$$

The parameter a determines whether the entropy measure in equation (1) gives priority to the absolute variety of functional experience (low values of a) or to the evenness of the distribution of functional

experience (high values of a). A number of entropy indices can be derived by variations of a .⁹ We calculate our indices of *variety* and *diversity* with $a = 0$ and $a \rightarrow +\infty$, respectively. Hence, for *variety*, equation (2) evolves to

$$\text{Variety} \equiv v_0(s) = \sum_{i=1}^n s_i^0 = z \leq n, \quad (3)$$

where z denotes the number of functional categories in which at least one member of the start-up team has prior work experience.¹⁰ The *variety* index is normalized and ranges from 0 (low variety) to 1 (high variety).

With a approaching infinity, equation (2) evolves to

$$\text{Diversity} \equiv v_{+\infty}(s) = 1/\max(s_i). \quad (4)$$

Accordingly, our measure of *diversity* is determined by the weighted probability of those functional categories in which the start-up team is experienced the most. It thus captures the (de-)concentration of a team's prior work experience in different functional categories. Contrary to the *variety* measure, *diversity* is a relative measure paying attention to the distribution of prior work experience among team members. We normalized the measure, so that it ranges from 0 (low diversity) to 1 (high diversity).

Finally, *knowledge scope* is computed by taking the mean of the variety and diversity indices. Higher values for knowledge scope indicate a broader and less concentrated knowledge base of a start-up team.

3.3.2 Knowledge Disparity

Our measure of *dissimilarity* is based on pairwise comparisons of team members' functional background patterns. For two members A and B of a start-up team, this can be formalized as

$$f_i^{A,B} = \begin{cases} 1 & \text{if } x_i^A = 1 \wedge x_i^B = 1 \text{ for all } i \in N \wedge i \in [1, \dots, n] \\ 0 & \text{otherwise.} \end{cases}$$

Summing f_i over all functional categories, we receive $F^{A,B} = \sum_{i=1}^n f_i^{A,B}$, denoting the number of categories team members A and B share prior work experience in. To obtain a *dissimilarity* measure, we compare this overlap of functional experiences of team members A and B with the potential overlap given their individual functional backgrounds. Thus, *dissimilarity* in functional backgrounds of team members A and B can be calculated by

⁹ For example, one obtains the Teachman (1980) index for $a = 1$, or the Herfindahl-Hirschman index for $a = 2$ (Herfindahl, 1950; Hirschman, 1964).

¹⁰ Note that for $s_i=0$, equation (3) is not defined as Baumgärtner's (2004) entropy measure only takes account of functional categories which are effectively occupied. In the context of our study, this might be of concern since it is most likely that entrepreneurial teams are experienced in some categories but not in others. Therefore, equation (3) is only calculated for those functional categories in which at least one team member gained prior work experience.

$$Dissimilarity^{A,B} = 1 - \frac{F^{A,B}}{(\sum_{i=1}^n x_i^A + \sum_{i=1}^n x_i^B) / 2}. \quad (5)$$

This variable ranges from 0, indicating complete overlap/similarity of functional backgrounds, to 1, indicating complete dissimilarity of the functional backgrounds of team members A and B. By taking the mean of all pairwise dissimilarity measures, we obtain the *dissimilarity* index at the team level. Generally, the higher the value of dissimilarity, the more disperse is the start-up team's knowledge base.

Our *non-redundancy* index builds on the conceptualization of *variety* described above. Here, the number of functional categories z in which at least one team member is reported to have prior work experience is weighted with the total number of functional experiences the team possesses in the z categories. Hence, *non-redundancy* is defined as

$$Non-redundancy = z / \sum_{i=1}^n \sum_{j=1}^m x_{ij}. \quad (6)$$

Non-redundancy indicates the extent to which team members' functional experiences exceed the level necessary to maintain a certain *variety* in functional experiences within the start-up team. This index is normalized, ranging from 0 (low non-redundancy) to 1 (high non-redundancy). The higher the value for *non-redundancy*, the smaller is the team members' shared experience in the different functional categories.

By taking the mean of the dissimilarity and non-redundancy indices, we finally derive our measure of *knowledge disparity*. High values of knowledge disparity indicate more pronounced differences within the knowledge stocks of start-up team members.

3.3.3 Traditional Functional Heterogeneity

In order to compare our proposed two-dimensional measurement of team heterogeneity with the established unidimensional approach, we estimate a *traditional functional heterogeneity* measure. Based on a modified version of Blau's (1977) index, *traditional functional heterogeneity* is computed by

$$1 - (\sum_{i=1}^n s_i^2), \quad (7)$$

where s_i is the weighted share of team members' experience in a given category i from equation (2). This unidimensional measure is normalized, ranging from 0 (low traditional functional heterogeneity) to 1 (high traditional functional heterogeneity).

3.4 Control Variables

Furthermore, our unique dataset provides the opportunity to control for a variety of other factors in order to more accurately assess the influence of the knowledge scope and knowledge disparity dimensions of team heterogeneity on start-up teams' entrepreneurial and innovative performance. In doing so, we apply Blau's (1977) original index to consider *age heterogeneity* (based on team members' age in seven age categories), *industry experience heterogeneity* (based on dichotomous

variables indicating whether or not each team member has prior industry experience), and *gender heterogeneity* (Chowdhury, 2005; Eisenhardt & Schoonhoven, 1990; Hambrick et al., 1996; Williams & O'Reilly, 1998). Other than in previous studies, we do not consider *ethnic heterogeneity* because virtually no member of a start-up team in our sample belonged to an ethnic minority. This is not surprising, though, given the high degree of ethnic homogeneity of the general population in the German federal state of Thuringia (Statistisches Bundesamt, 2008).

There are reasons to believe that relationships among team members impact new venture performance (Francis & Sandberg, 2000). Accordingly, start-up teams' *relational composition* is also taken into consideration (Ruef et al., 2003). Relationships among start-up team members at the time of start-up are assessed with several categories (1 = spouse or partner; 2 = relative; 3 = friend or colleague from previous employment; 4 = acquaintance; 5 = stranger). The relational composition index is computed by taking the mean of all pairwise combinations among the start-up team members.

Research has shown that larger start-up teams are more likely to encompass heterogeneous perspectives, knowledge stocks, and personal goals (Ancona & Caldwell, 1992; Ucbasaran et al., 2003). Larger teams have also been linked to higher growth of start-ups (Eisenhardt & Schoonhoven, 1990). Hence, we control for *team size* as the number of team members at the time of new venture creation.

Also, following past research on small firm growth and development (e.g., Baum et al., 2001; Chandler & Hanks, 1993; Cooper et al., 1994), we include control variables referring to *start-up capital* (total amount of financial capital available at the start of the first business year) and *industry sector* (dummy variables). Additionally, we include a series of dummy variables controlling for potential effects of the *start-up year* on the new venture's performance.

Innovative new ventures are faced with unique challenges when securing the financial, organizational, and managerial resources needed for growth and survival (Audretsch, 2000). Because of these potentially confounding influences, we control for the *innovativeness* of the start-up (1 = conducting R&D was a major activity in the venture creation phase as well as in the first three years of business operation; 0 = otherwise).

We finally control for *growth aspirations* of the start-up team because prior research has linked higher growth aspirations with higher levels of subsequent new venture growth (Naffziger et al., 1994). Growth aspirations at the time of firm formation are measured dichotomously (1 = the new firm should have become a market leader; 0 = the new firm should have remained a small-scale competitor).

3.5 Cross-Validation of Interviewees' Responses

The data for our study are collected from self-reports of the start-up team's lead entrepreneur on one questionnaire, which can have limitations (Podsakoff & Organ, 1986). Thus, the primary potential limitation of our newly-developed measurement of start-up team heterogeneity is a common-method bias. In order to strengthen our case and to validate the core independent variables, we conducted additional face-to-face interviews with a second team member, applying the same questionnaire. These data were gathered for a random subsample of 48 start-up teams. Dependent t-tests for paired samples did not reveal significant differences with respect to our four heterogeneity indices *variety* ($t = -1.25$; p

= .22), *diversity* ($t = -.70$; $p = .49$), *dissimilarity* ($t = -.48$; $p = .11$), and *non-redundancy* ($t = -.94$; $p = .36$), indicating validity of our measurement of start-up team heterogeneity.

4. Results

4.1 Descriptive Results and Factor Analysis

Table 1 presents descriptive statistics and correlations for all variables included in this study. As can be seen, the team start-ups in our sample on average applied for 1.81 patents in the first four business years, and had 8.42 employees at the end of the third year of business operation. Furthermore, we find the sampled team start-ups to show a high survival rate with 92% of these firms surviving the first three business years. The average team size was 2.81 members, with 46% of the start-up teams consisting of two members, 34% of three members, 13% of four members, and 7% of five or more members. A mean value of 3.18 for the relational composition further indicates that these teams in most cases consisted of friends or colleagues from previous employment. Hence, unlike other datasets (e.g., PSED I and II), our sample does not contain a large proportion of ‘romantic teams’ (only 6% of our teams consist of spouses), which have been shown to skew results (Ruef et al., 2003).

[Table 1 about here]

[Table 2 about here]

As expected, our indices of *variety* and *diversity* are highly correlated ($r = .83$). The same holds true for the indices of *dissimilarity* and *non-redundancy* ($r = .82$). Interestingly enough, both pairs of heterogeneity indices show low correlations, ranging from $r = .03$ to $r = .12$. While preliminary, these findings offer some initial support for our two-dimensional measurement of start-up team heterogeneity. An exploratory factor analysis is thus performed to assess the discriminant and convergent validity of two distinct heterogeneity dimensions. A principal component analysis with Varimax rotation reveals that the four heterogeneity indices *variety*, *diversity*, *dissimilarity*, and *non-redundancy* can indeed be reduced to two factors which correspond to the two theoretically-specified team heterogeneity dimensions *knowledge scope* and *knowledge disparity* (see Table 2). More specifically, *variety* and *diversity* load on *knowledge scope* (factor loadings .957 and .953, respectively), explaining 50.14% of the variance. The indices for *dissimilarity* and *non-redundancy* load on *knowledge disparity* (factor loadings .951 and .955, respectively), explaining another 41.16% of the variance. There is thus strong support for our contention of team heterogeneity as a two-dimensional concept.¹¹

4.2 Regression Analysis and Results

In order to test for our hypotheses, we pursue the following empirical strategy. Our first indicator of team start-ups’ entrepreneurial performance – venture survival – is dichotomous in nature. We

¹¹ For our empirical analysis, we use the original variables instead of the factor loadings.

therefore employ logistic regression in this step of the analysis. The second indicator of entrepreneurial performance – employment growth – and the indicator of team start-ups' innovative performance – the number of patent applications – involve count data. Descriptive statistics in Table 1 reveal that for both of these dependent variables the variance exceeds the mean, suggesting the presence of overdispersion. If this is the case, the standard errors of parameters will be underestimated, resulting in spuriously higher levels of statistical significance. A likelihood ratio test indeed provides evidence to conclude that overdispersion is given for both employment growth and the number of patent applications. In order to correct for overdispersion in our data on employment growth, we use negative binomial models (Hausman et al., 1984). Regarding the patent data, another concern is the high frequency of zeros (approximately 85% of the sampled team start-ups did not apply for any patents during the first four business years), suggesting the use of zero-inflated negative binomial models (Greene, 2003). In order to select between negative binomial and zero-inflated negative binomial models, we run the Vuong (1989) test. Test statistics indicate that zero-inflated negative binomial models fit the patent data better. The regression results for all three performance indicators are displayed in Tables 3–5.

[Table 3 about here]

[Table 4 about here]

Our analysis first examines determinants of new venture survival (Table 3). Model 1 includes all control variables relating to the new venture team and to the new venture project. Model 2 adds the core independent variables *knowledge scope* and *knowledge disparity*. In both models, control variables do not show up as significant. Looking at Model 2, *knowledge scope* – the breadth of a start-up team's knowledge base – does not significantly affect new venture survival. Moreover, we find start-up teams' *knowledge disparity* – the divergences in team members' functional background patterns – to be a significant negative predictor of venture survival ($p < .05$).

Turning to Table 4, we replicate the structure of analysis employed above using employment growth as the dependent variable. Regarding the control variables in Model 1, we find several significant estimates. Accordingly, start-up teams with lower levels of *industry experience heterogeneity* ($p < .05$) and higher levels of *age heterogeneity* ($p < .01$) are more likely to grow their ventures in the first three business years. We also find the amount of *start-up capital* ($p < .01$) and *growth aspirations* ($p < .05$) to positively predict employment growth in the first three years after start-up. These control variables retain their significance in Model 2 as well. Furthermore, in Model 2, *knowledge scope* has a positive effect ($p < .01$), while *knowledge disparity* does not significantly predict the number of employees in the third business year. Summing up, the results for both indicators of start-up teams' entrepreneurial performance provide partial support for Hypotheses *H1a* and *H1b*.

[Table 5 about here]

Finally, determinants of team start-ups' innovative performance are investigated (Table 5). In Model 1, *team size* ($p < .05$), *start-up capital* ($p < .10$), and *growth aspirations* ($p < .10$) emerge as significant positive predictors. Although *innovativeness* of the start-up does not significantly relate to the number of patent applications, one cannot completely rule out *innovativeness* as an important predictor of innovative firm performance. Indeed, the negative sign of the *innovativeness* coefficient ($p < .01$) provided by the auxiliary logit regression suggests that a high degree of *innovativeness* increases the likelihood of a team start-up being in the “not always zero” group and, thus, applying for at least one patent in the first four business years.¹² In Model 2, only *start-up capital* ($p < .10$) remained significant. Furthermore, we find the *innovativeness* of the team start-up ($p < .10$) to show a positive effect. Supporting Hypothesis *H2a*, *knowledge scope* ($p < .05$) and *knowledge scope squared* ($p < .05$) significantly contribute to the explanation of the number of patents applied for by the start-up team, with the maximum being reached at a value of .47 for *knowledge scope*. As expected in Hypothesis *H2b*, we also find a negative effect of *knowledge disparity* ($p < .05$).

Our results are robust with respect to several modifications of the regression models.¹³ First, running all regressions for different team sizes does not change the directions of the coefficients of *knowledge scope* and *knowledge disparity*. However, due to reduced sample sizes, significance levels decrease slightly. Second, controlling for the entry and exit of team members during the venture creation process does not alter our results either. Third, we also consider *knowledge disparity squared* as a predictor of team start-ups' innovative performance as well as *knowledge disparity squared* and *knowledge scope squared* as predictors of team start-ups' entrepreneurial performance. While we do not have theoretical arguments to expect any particular relationships, the respective coefficients turn out to be insignificant and are therefore not reported in the regression tables.

4.3 Supplementary Analysis: The Unidimensional Approach to Heterogeneity

In an additional analysis, we compare our proposed two-dimensional measurement of team heterogeneity with the conservative unidimensional approach. We therefore re-run the regressions for our three dependent variables (venture survival, employment growth, number of patent applications) using *traditional functional heterogeneity* instead of *knowledge scope* and *knowledge disparity* as the core independent variable. The results are displayed in Model 3 in Tables 3–5. Except for employment growth in the first three business years ($p < .05$; Table 4), *traditional functional heterogeneity* is found to be insignificant. Furthermore, for all three dependent variables, models containing *knowledge scope* and *knowledge disparity* achieve larger explanatory power (as indicated by pseudo R^2) compared to models containing *traditional functional heterogeneity* as the core independent variable.

Using Akaike's (1973) information criteria (AIC), we further compare the goodness-of-fit of the models including *knowledge scope* and *knowledge disparity* (Model 2 in Tables 3–5) with those including *traditional functional heterogeneity* (Model 3 in Tables 3–5). Throughout, the AIC provides support for the use of the proposed two-dimensional heterogeneity measurement as opposed to the traditional unidimensional heterogeneity measure.

¹² A zero-inflated negative binomial model consists of two nested models. The auxiliary logit regression in Table 5 estimates the probability of a team start-up applying for at least one patent, while the negative binomial model explains the variance in patent counts within the group of patent applicants.

¹³ The respective results are available from the authors.

5. Discussion

5.1 Interpretation of the Results

The objective of our study was to reconcile the inconclusive results of prior research on the connection between functional heterogeneity of new venture teams and subsequent new venture performance. Therefore, we draw on recent theoretical and methodological advancements in the fields of top management team and entrepreneurial team research, showing that different conceptualizations of team heterogeneity yield different effects on team processes and outcomes (see e.g., Bunderson, 2005; Bunderson & Sutcliff, 2002; Liao et al., 2009). We contribute to this literature by providing empirical evidence for two separate dimensions of functional team heterogeneity, which both affect new venture performance differently.

Consistent with a cognitive resource perspective on teams (e.g., Cox & Blake, 1991; Hambrick & Mason, 1984), the *knowledge scope* dimension of functional heterogeneity appeared to positively relate to new ventures' entrepreneurial performance. Drawing from theories on social similarity and attraction (Byrne, 1971; Hogg & Abrams, 1998; Tajfel & Turner, 1986), the *knowledge disparity* dimension showed a negative effect on entrepreneurial performance. There are two aspects that deserve closer attention. Interestingly, we found *knowledge disparity* to reduce survival chances of newly-founded businesses, whereas this dimension of team heterogeneity did not affect new venture growth. In contrast, *knowledge scope* did not affect survival but predicted the growth of the new venture in the first three years of business operation. It seems that for setting up and maintaining a new venture, arguably the minimum criterion for entrepreneurial success, an entrepreneurial team needs cohesion, trust, and a 'common language' and, thus, a low degree of disparity (or a high degree of similarity) in the functional background experiences. If, on the other hand, the new venture is to grow in the first years of business operation, the start-up team needs to leverage the benefits of a diverse stock of knowledge, capabilities, and expertise provided by a broad scope of functional experience. These results are in line with prior work on new venture team formation and nascent venture success. For example, Ruef et al. (2003) find that social similarity among team members (in terms of gender and ethnic homogeneity) seems to be the most important driver of team formation. Liao et al. (2009) show that social similarity, but not functional heterogeneity, within a new venture team contributed to getting an emerging business up and running. However, they argued that a broad knowledge stock "may become increasingly more important as the venture evolves into a larger business" (p. 13).

Moreover, we were interested in the effects of both heterogeneity dimensions on the innovative performance of team start-ups. As expected, we found evidence for an inverse U-shaped relationship between *knowledge scope* and the number of patents applied for in the first four business years. Firm innovation turned out to be highest at a moderate level of an entrepreneurial team's breadth in functional experience. This is consistent with related research on R&D alliances (Sampson, 2007), which shows that firms reap most innovative benefits from collaborative R&D when cooperation partners have some, but not all, capabilities in common. Bringing these findings together, we can speculate that an overly-narrow knowledge stock of a start-up team (as might be given in a team consisting of three engineers) restrains the potential for knowledge creation because there is not much team members can learn from each other. On the other hand, members of a start-up team with an overly-broad knowledge stock (i.e., a team formed by a marketing expert, an engineer, and a financing expert) might find it difficult to learn from each other because of a missing common frame of reference to build on. Extending this line of reasoning, we also find that *knowledge disparity*

negatively related to innovative team performance. Irrespective of the level of *knowledge scope*, it was some overlap in team members' functional background (referring to a low level of *knowledge disparity*) that might have been crucial for effective communication and mutual understanding among team members and, ultimately, team innovation. Without any functional overlap (referring to a high level of *knowledge disparity*), the start-up team might have been likely to suffer from unfavorable social categorization processes, distrust, and stereotyping (Tajfel & Turner, 1986), which then could have impaired innovative performance.

Finally, we examined the goodness-of-fit between the conservative unidimensional measurement of team heterogeneity and its hypothesized two-dimensional conceptualization. In all models, our two-dimensional approach to heterogeneity fitted the data better (as indicated by lower values for Akaike's (1973) information criteria (AIC)), suggesting the superiority of the measurement concept proposed in this paper. Additionally, using *knowledge scope* and *knowledge disparity* instead of *traditional functional heterogeneity* as core independent variables provided statistically significant results which are in line with theoretical expectations. In particular, our findings for innovative team performance indicated that a unidimensional measurement concept might comprise countervailing effects of functional team heterogeneity, resulting in an insignificant net effect. This supports earlier research in organizational demography (Pfeffer, 1983), arguing that a better match of theory and construct measurement is a necessary precondition for understanding the complex relations of individuals in organizational settings.

5.2 Implications for Practice

For prospective entrepreneurs, the present study suggests that, when forming a team, a fit between team goals and team structure should be considered. However, entrepreneurs more frequently compose teams based on mutual interest and attraction rather than on complementary capabilities (Ruef et al., 2003). Hence, start-up teams usually do not possess all of the relevant competences and resources required for new venture success. For example, a university-based start-up team formed by a group of scientists may have a strong technological knowledge base but probably lacks industry-specific and managerial background experiences. One mechanism to fill this knowledge gap and, thus, to broaden the team's *knowledge scope* is the adding of new team members endowed with the lacking commercial competences (Chandler et al., 2005; Forbes et al., 2006; Vanaelst et al., 2006). In the light of our findings, these commercially-experienced team members, so-called "surrogate entrepreneurs" (Franklin et al., 2001), also need to have some technological competences to secure sufficient overlap of the functional background experiences with the original team members. While avoiding the drawbacks of an increased *knowledge disparity*, new team members would then be able to comprehend the technological base of the products that they will be marketing and to draw on a 'common ground' for communication with the scientist team members.

Another way to achieve a broader *knowledge scope* in a start-up team resides in learning processes (Chandler & Lyon, 2009). Accordingly, engineers and researchers who have been engaged in the development of the new venture's technological basis can gain business-related knowledge vicariously through learning from the actions of their commercially-experienced team members. Vicarious learning can also take place by attending seminars, workshops, and other structured educational experiences such as formal university-based training. Referring to this, the present study speaks in favor of including elements of interdisciplinary cooperation in entrepreneurship education and training. Educational programs on cooperative teamwork between engineering and business

management students provide an opportunity for interdisciplinary learning and can help reduce stereotypical assumptions and ease mutual understanding (Lüthke & Prügl, 2006). In this way, prospective entrepreneurs would be better prepared for engaging in functionally heterogeneous start-up teams.

This study may also inform the practices of venture capitalists who consistently consider start-up team composition as an important funding criterion (Cyr et al., 2000). Depending on the funding strategy of the venture capitalist, there are two particular implications from our research. First, profit maximizing private venture capitalists, earning the bulk of their returns with a few investments in their portfolios (Gompers & Lerner, 2004), might raise the growth potential of their investments by focusing on the prevalence of a broad *knowledge scope*, irrespective of potentially overlapping functional experiences (low *knowledge disparity*) in team members' job histories. Second, public venture capitalists might emphasize low levels of *knowledge disparity* within the entrepreneurial team in order to reduce the default risk of their investments. In doing so, public venture capitalists might reduce the overall risk of their portfolios and contribute to their public investors' targets such as fostering (regional) economic growth (Manigart et al., 2002).

5.3 Limitations and Future Research

Our study has several limitations which might however provide promising opportunities for future investigations. First and most importantly, our cross-sectional study is mainly based on retrospective data. Although we adopted the Life History Calendar method to facilitate the recall process and to ensure the validity of our data (Belli et al., 2004; Caspi et al., 1996), longitudinal data are needed to strengthen causal inferences regarding the relationships we observed. The fact that, in our analyses, start-up team characteristics at the time of firm formation are linked to new venture performance three years after start-up at least suggests that causality might work in the direction hypothesized: start-up teams' *knowledge scope* and *knowledge disparity* shape new venture performance. Second, in the present study, common-method bias might result from the use of self-reported data from the same source, the lead entrepreneur of each start-up team. We mitigated this problem by accessing patent data in order to derive an objective and well-established measure of innovative firm performance. Secondary data from external business information providers enabled us to validate our measure of employment growth. Furthermore, for a small sub-sample of team start-ups, we gathered additional interview data from a second team member in order to validate our core independent variables *knowledge scope* and *knowledge disparity*. A third caveat is that the present study is limited to team start-ups in the German federal state of Thuringia. This might raise the question of transferability of results to other national contexts. While our study is not internationally comparative in nature and therefore cannot offer any answers to this question, the conceptual model of new venture team functional heterogeneity presented in this paper is not country-specific, but rather is grounded in international scholarly work and established empirical findings. Finally, only direct effects of *knowledge scope* and *knowledge disparity* on start-up performance were investigated. In fact, recent research has begun to consider how (via what mediators) and when (in the presence of what moderators) entrepreneurial teams' functional heterogeneity might lead to higher or lower firm performance. While clearly beyond the scope of our study, future research may find these aspects in connection with the proposed two heterogeneity dimensions worth studying.

6. Conclusion

Besides these limitations, this study contributes to one of the still-unresolved questions in the entrepreneurial team literature: Does functional team heterogeneity help or hinder new venture performance? The answer we provide draws from a new conceptual approach to disentangle two separate dimensions of functional team heterogeneity, namely knowledge scope and knowledge disparity. Our empirical analysis suggests, however, that this answer is not a holistic one but rather depends on the team performance criterion considered. For example, while a start-up team's knowledge disparity negatively relates to survival but does not affect growth of the new venture, knowledge scope does not affect survival but contributes to new venture growth. Composing a successful new venture team thus requires more than just finding the optimal trade-off point in a unidimensional heterogeneity-homogeneity continuum.

Table 1:
Descriptive Statistics and Correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) # of patent applications	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(2) Survival	.05	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(3) # of employees	.00	.10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(4) Variety	.00	-.07	.12 *	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(5) Diversity	-.04	-.05	.13 *	.83 *	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(6) Dissimilarity	-.06	-.15 *	.04	.12 *	.10	-	-	-	-	-	-	-	-	-	-	-	-	-
(7) Non-redundancy	-.16 *	-.11	.05	.03	.11 *	.82 *	-	-	-	-	-	-	-	-	-	-	-	-
(8) Knowledge scope	-.02	-.07	.14 *	.96 *	.95 *	.11 *	.07	-	-	-	-	-	-	-	-	-	-	-
(9) Knowledge scope squared	-.03	-.04	.14 *	.89 *	.96 *	.03	.02	.10 *	-	-	-	-	-	-	-	-	-	-
(10) Knowledge disparity	-.11 *	-.14 *	.05	.08	.11 *	.96 *	.94 *	.10	.02	-	-	-	-	-	-	-	-	-
(11) Traditional functional heterogeneity	.01	-.10	.11	.88 *	.77 *	.29 *	.19 *	.87 *	.72 *	.26 *	-	-	-	-	-	-	-	-
(12) Traditional functional heterogeneity squared	-.00	-.09	.12 *	.95 *	.86 *	.23 *	.15 *	.95 *	.84 *	.20 *	.96 *	-	-	-	-	-	-	-
(13) Team size	.24 *	.02	-.03	.10	-.16 *	-.03	-.51 *	-.02	-.06	-.26 *	.02	-.01	-	-	-	-	-	-
(14) Industry experience heterogeneity	-.02	-.03	-.09	.11 *	.04	.15 *	.14 *	.08	.05	.15 *	.12 *	.11 *	-.01	-	-	-	-	-
(15) Age heterogeneity	.13 *	-.00	.08	.03	-.02	.05	-.10	.01	-.02	-.02	.05	.04	.25 *	.04	-	-	-	-
(16) Gender heterogeneity	.12 *	-.03	-.03	.04	.02	.06	-.06	.03	.02	.00	.02	.03	.17 *	.08	.02	-	-	-
(17) Relational composition	.02	-.07	.02	.05	-.05	-.05	-.19 *	.00	.00	-.12 *	.01	.01	.27 *	-.06	.07	-.22	-	-
(18) Innovativeness	.20 *	.02	.01	.03	-.07	.02	-.03	-.02	-.02	-.00	.01	-.02	.13 *	.09	.04	-.02	.08	-
(19) Start-up capital	.14 *	-.08	.30 *	.19 *	.13 *	.11	.06	.17 *	.15 *	.09	.18 *	.18 *	.05	.04	.07	-.04	.13 *	.18 *
(20) Growth aspirations	.13 *	.02	.10	.02	.05	-.03	-.03	.04	.05	-.03	.00	.01	-.00	.01	-.01	-.07	-.04	.19 *
Mean	1.81	.92	8.42	.68	.48	.47	.54	.58	.42	.50	.82	.51	2.81	.25	.45	.09	.43	3.37
SD	9.97	.28	13.67	.31	.28	.32	.26	.28	.31	.28	.23	.19	.90	.41	.31	.18	.50	1.37

Note: * denotes a significance level of 5%.

Table 2:
Results of Factor Analysis on Team Heterogeneity Dimensions

	Knowledge Scope	Knowledge Disparity
Variety	.957	.027
Diversity	.953	.067
Dissimilarity	.070	.951
Non-redundancy	.024	.955

Note: Exploratory factor analysis; Principal component analysis with varimax rotation.

Table 3:
Start-up Team Heterogeneity and New Venture Survival

	Dependent variable: New venture survival ^a		
	(I)	(II)	(III)
<i>Two-dimensional approach to heterogeneity</i>			
Knowledge scope	----	-0.123	----
Knowledge disparity	----	-0.481 **	----
<i>Unidimensional approach to heterogeneity</i>			
Traditional functional heterogeneity	----	----	-0.474
<i>Control variables regarding the new venture team</i>			
Industry experience heterogeneity	-0.116	-0.045	-0.081
Age heterogeneity	0.040	0.060	0.026
Gender heterogeneity	-0.179	-0.168	-0.170
Relational composition	-0.300	-0.321	-0.295
Team size	0.182	0.040	0.190
<i>Control variables regarding the new venture project</i>			
Innovativeness	0.154	0.119	0.126
Start-up capital	-0.287	-0.231	-0.239
Growth aspirations	0.071	0.049	0.075
Time dummies / industry dummies	No/No	No/No	No/No
Constant	2.551 ***	2.643 ***	2.622 ***
Alpha	----	----	----
Pseudo R ²	0.046	0.074	0.056
AIC	214.109	212.557	213.573
Chi ²	17.636	25.314	19.710
N	337	337	337

^a Logistic regression, coefficients reported; *** (**, *) denote a significance level of 1% (5%, 10%)

Table 4:
Start-up Team Heterogeneity and Employment Growth

	Dependent variable: Number of employees in the 3 rd business year ^a		
	(I)	(II)	(III)
<i>Two-dimensional approach to heterogeneity</i>			
Knowledge scope	-----	0.157 ***	-----
Knowledge disparity	-----	0.085	-----
<i>Unidimensional approach to heterogeneity</i>			
Traditional functional heterogeneity	-----	-----	0.143 **
<i>Control variables regarding the new venture team</i>			
Industry experience heterogeneity	-0.124 **	-0.139 **	-0.136 **
Age heterogeneity	0.167 ***	0.171 ***	0.169 ***
Gender heterogeneity	0.043	0.045	0.044
Relational composition	0.062	0.072	0.073
Team size	-0.056	-0.029	-0.062
<i>Control variables regarding the new venture project</i>			
Innovativeness	-0.024	-0.022	-0.022
Start-up capital	0.325 ***	0.306 ***	0.302 ***
Growth aspirations	0.134 **	0.145 **	0.146 **
Time dummies / industry dummies	Yes/Yes	Yes/Yes	Yes/Yes
Constant	1.959 ***	1.944 ***	1.950 ***
Alpha	0.871	0.840	0.854
Likelihood ratio test	1871.52 ***	1792.65 ***	1807.78 ***
Pseudo R ²	0.046	0.051	0.049
AIC	2076.01	2069.68	2072.13
Chi ²	98.743	109.071	104.623
N	337	337	337

^a Negative binomial regression; *** (**,*) denote a significance level of 1% (5%, 10%)

Table 5:
Start-up Team Heterogeneity and Number of Patent Applications

	Dependent variable: Number of patent applications in the first 4 business years ^a		
	(I)	(II)	(III)
<i>Two-dimensional approach to heterogeneity</i>			
Knowledge scope	----	1.723 **	----
Knowledge scope squared	----	-1.690 **	
Knowledge disparity	----	-0.633 **	----
<i>Unidimensional approach to heterogeneity</i>			
Traditional functional heterogeneity	----	----	-0.054
Traditional functional heterogeneity squared	----	----	0.285
<i>Control variables regarding the new venture team</i>			
Industry experience heterogeneity	0.021	0.148	-0.040
Age heterogeneity	0.031	0.129	0.074
Gender heterogeneity	0.006	-0.057	-0.084
Relational composition	-0.228	-0.179	-0.292
Team size	0.707 **	0.431	0.720 ***
<i>Control variables regarding the new venture project</i>			
Innovativeness	0.373	0.781 *	0.401
Start-up capital	0.349 *	0.340 *	0.291 *
Growth aspirations	0.368 *	0.300	0.395 **
Time dummies / industry dummies	No/Yes	No/Yes	No/Yes
Constant	0.785	0.305	0.815 *
<i>Auxiliary regression (logit model)</i>			
Innovativeness	-1.248 ***	-1.046 ***	-1.222 ***
Constant	1.660 ***	1.500 ***	1.730 ***
Alpha	1.356	1.105	1.119
Likelihood ratio test	225.27 ***	157.61 ***	190.65 ***
Vuong test	1.75 **	1.30 *	1.75 **
Pseudo R ²	0.095	0.100	0.091
AIC	570.194	568.795	572.436
Chi ²	38.04	43.76	38.12
N	337	337	337

^a Zero-inflated negative binomial regression; *** (**, *) denote a significance level of 1% (5%, 10%)

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Appendix

In Table A1, an illustrative example of a start-up team with three members A, B, and C is provided. A team member is experienced in one of the six functional categories when the respective cell takes the value of 1. The resulting weighted probabilities s_i in the last column of Table A1 are calculated according to equation (2). Table A2 shows the values obtained for our four heterogeneity indices.

Table A1:
Start-up Team with Heterogeneous Functional Experience

Functional categories	Start-up team members			s_i
	A	B	C	
Management	1	1	1	.3
Marketing / Sales / Promotion	1	0	0	.1
Accounting / Controlling / Financing	0	0	0	.0
Engineering / R&D	1	0	0	.1
Production	1	1	1	.3
Personnel	1	1	0	.2

Variety. The start-up team in Table A1 has a rather broad functional background with member A being experienced in five functional categories, only leaving uncovered “accounting or controlling or financing”. Team members B and C are experienced in a total of three functional categories which, however, completely overlap with the experience categories of A. Therefore, as indicated by equation (3), our measure of variety takes the value of 5 with a normalized value of .8.

Diversity. “Management” and “production” are the functional categories in which all team members are experienced. With team members’ prior experiences adding up to ten covered cells in Table A1, both of these functional categories achieve a weighted probability s_i of .3. Following equation (4), this team possesses a moderately diverse functional background which manifests in a diversity value of 3.33 and a normalized diversity value of .47, respectively.

Dissimilarity. Table A1 shows rather similar functional experience patterns for team members B and C, sharing knowledge in two of their three functional categories. In contrast, the functional experience pattern of team member A differs from that of B and is even more different to that of C. Pairwise measurements following equation (5) provide dissimilarity values of .43 for the combination A-C, .25 for A-B, and .20 for B-C. Taking the mean of all three pairwise dissimilarity values provides a dissimilarity value at the team-level of .29. Dissimilarity is bound to a unit interval per definition.

Non-redundancy. The distribution of prior experiences across the different functional categories in Table A1 suggests that the start-up team could abandon the experiences of members B and C without reducing the total number of functional categories the team would be experienced in. Given that B and C contribute five out of the team’s ten covered cells in Table A1, equation (6) provides a non-redundancy value of .5 (normalized .38).

Table A2:

Resulting Values for the Heterogeneity Indices

	Theoretical minimum	Theoretical maximum	Values from the example	
			Original	Normalized to unit interval
Variety	1	$z=6$	5.00	0.80
Diversity	1	$z=6$	3.33	0.47
Dissimilarity	0	1	0.29	0.29
Non-redundancy	$z/(m*n)$	1	0.50	0.38