Organizational Divide, Demographic Divide, and Performance of R&D Teams:

A Fuzzy-set Qualitative Comparative Analysis

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Joint R&D teams composed of members from different organizations face a dilemma. Diverse skills, knowledge stocks, and perspectives can be combined productively but the team members' differing organizational backgrounds may create conflict and inhibit information sharing, thus endangering the potential benefits from joint R&D. We propose and test a new model that links R&D team composition with performance. The model is based on the interaction of two divides caused by team composition. The problems posed by the organizational divide in joint teams may be overcome by a demographic divide based on age, gender, and educational background. While a demographic divide is universally beneficial to R&D performance, it is indispensable in joint teams: Only if the demographic divide cuts across the organizational divide may joint teams achieve high performance. In addition, a necessary condition for high performance in any type of R&D team is a high degree of information sharing. We test our hypotheses with archival and survey data from 51 projects conducted either by joint or by unilateral teams within one long-standing company-university R&D partnership. In a fuzzy-set qualitative comparative analysis, we find strong support for our model. In particular, if members share information and a demographic divide exists, both joint and unilateral teams achieve high performance. But if a demographic divide is lacking, only unilateral teams perform well, while the joint teams perform particularly badly. These findings have important implications for composing R&D teams in an era of open innovation.

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Companies increasingly rely on collaborative research and development (R&D) in order to spread risks, shorten development times, and access inputs from other organizations. They pool knowledge from different sources and bring together unique perspectives, resources, and expertise (Du Chatenier et al. 2009, Chesbrough 2003, Powell et al. 1996). Companies engage in collaborative R&D by forming strategic alliances (Hagedoorn 2002) and by cooperating with universities (Roberts 2001).

At the core of collaborative R&D or "open innovation" (Chesbrough 2003) are joint R&D teams: groups of employees from more than one organization who collaborate in projects of knowledge creation such as product development or scientific publication (Bstieler and Hemmert 2010). Despite their proliferation, joint R&D teams are a "double-edged sword" (Milliken and Martins 1996). Bringing together the insights of employees from different organizations may enhance R&D performance because complementary knowledge can be combined in new ways, thus allowing creative, novel solutions that could not be achieved by one organization alone. At the same time, collaboration across organizations is difficult (Dyer et al. 2004), and some researchers doubt that R&D in joint teams pays off at all (Newell and Swan 2000, Sethi et al. 2002). The issue how joint R&D teams may reap the benefits while avoiding the problems of collaboration is largely unresolved.

According to recent research on team diversity, the ability to capitalize on heterogeneity depends on group composition, and, more specifically, on the existence and salience of group divides (e.g., Jehn and Bezrukova 2010, Lau and Murnighan 2005, Van Knippenberg and Schippers 2007). Joint research teams may face two divides: one based on members' organizational affiliation (organizational divide), one based on members' demographic differences (demographic divide). As the organizational divide splits the team into subgroups based on organizational affiliation, the subgroups represent different, sometimes opposing interests. These groups are embedded in distinct organizational cultures, and may be accustomed to different routines. As a result, an organizational divide may impede team performance (Smith and Blanck 2002, Tidd et al. 2001), and the potential benefits from collaborative R&D may not materialize. Subgroups in research teams may also arise based on a demographic divide among team members. A demographic divide – or group faultline (Lau and Murnighan 1998) – splits a group into "relatively homogenous subgroups based on the group members' alignment along multiple attributes" (Bezrukova et al. 2009: 35), such as gender, age, and education. For example, in a team of two older men and two younger women, a strong demographic divide exists because age and gender align, suggesting two homogenous subgroups (older men – younger women). The more distinct the demographic divide, the greater the likelihood that subcategorizations occur. Empirical evidence on whether demographic divides disrupt group functioning (Bezrukova et al. 2009, Polzer et al. 2006, Lau and Murnighan 2005) or rather enhance team outcomes (Bezrukova et al. 2010, Gibson and Vermeulen 2003, Thatcher et al. 2003) remains ambiguous.

The purpose of this paper is to understand whether group divides may enhance R&D team performance, and if so, under which conditions. We extend prior research on group faultlines by differentiating between organizational and demographic divides. Demographic divides have been examined in the context of joint and sometimes cross-cultural teams before (Bouncken and Winkler 2010, Li and Hambrick 2005, Zander and Butler 2010). But in these studies, group faultlines were conceived as one single divide resulting from the alignment of both the organizational and the demographic composition of teams. We contribute to these findings in two ways. First, we argue that in R&D teams a demographic divide is beneficial because homogenous subgroups serve as supportive cohorts. Second, we introduce the notion of crosscutting divides, building on prior work on crosscutting dimensions of diversity (Marcus-Newhall et al. 1993, Sawyer et al. 2006). We show that if a demographic divide cuts across organizational boundaries, the downside of joint teams may be avoided: the organizational divide is then overcome by a healthy demographic divide.

After elaborating this idea, we test its implications on archival information and questionnaire survey data for 51 R&D project teams within one university-industry partnership that organizes research in the field of information and communication technology. To date, the majority of studies on divides in teams has been based on student samples and artificially created work groups. Our study adds to that literature and, more specifically, to the lack of research on group divides in R&D teams (for one exception see Gibson and Vermeulen 2003). Our empirical design is unique. Previous empirical studies have focused either on joint or on unilateral teams only. Our sample includes both types, so we can examine whether joint teams are different from unilateral teams and how the demographic divide changes the potential downsides of the organizational divide. At the same time, many factors that may influence R&D performance directly or moderate the effect of team composition on group performance are controlled for by design. According to recent meta-analyses by Horwitz and Horwitz (2007) and Joshi and Roh (2009), industry setting, occupational demography as well as team type, task interdependence, and task complexity influence the performance outcomes of team diversity. In our setting, all researchers are employed by one university or one company and work within the structure of a single partnership in one industry with a common set of occupation-level demographic composition. All teams' tasks are highly complex and highly interdependent. Furthermore, national culture, location, and governance mechanisms, which also influence R&D performance (Du Chatenier et al. 2009), can be assumed identical for all teams in our study.

We also apply for one of the first times a fuzzy-set qualitative comparative analysis (fsQCA) (Ragin 2000) to the analysis of teams (see for one previous study Bakker et al. 2010). FsQCA is a method that is appropriate for smaller samples and allows the study of complex causal links. This is exactly the context in which empirical studies on the links between team diversity and performance are usually conducted. The number of teams that can be compared is often limited, but the models usually suggest that the characteristics of teams may be interrelated in complex ways. In our context, the demographic divide is important in any R&D team – but they are indispensable in joint R&D teams. Hence, the importance of a characteristic depends on all other characteristics. Therefore, complex causality draws on a configurational approach based on typological thinking (Meyer et al. 1993). Testing hypotheses from a configurational approach is difficult with regression analysis but can be achieved by applying fsQCA (Fiss 2007).

Conceptual differences between organizational and demographic divides

In joint teams composed of members from different organizations, an organizational divide occurs. It is an a priori, pre-established demarcation, because it stems from the strategic decision to form a joint team. Common examples of joint teams are merger integration teams, joint venture management teams or, as in our case, collaborative research and development teams. Members of joint teams come as “representatives, or delegates, from a small number of (often just two) social entities and are aware of, and find salience in, their delegate status” (Li and Hambrick 2005, p. 794). Hence, an organizational divide implies the existence of distinct coalitions within a team (Hambrick et al. 2001).

Coalition members are embedded in the same organizational culture and may be used to the same routines. Although they may differ in terms of personal and educational background, coalition members pursue a common goal, i.e., to protect their organization’s interests (Hambrick et al. 2001). Hence, the coalitions in joint teams may pursue divergent, even conflicting interests and tend to compete against each other over resources (Bezrukova et al. 2009, Polzer et al. 1998, Thatcher et al. 2003). As Hambrick et al. (2001, p. 1038) note, “the existence of coalitions in a group generally causes members to be competitive, turf-conscious, and rigid”. The competition is likely to be especially fierce when partnering organizations pursue divergent goals. Thus, goal conflicts and disagreements about responsibilities appear to be more likely in joint teams (Elmuti and Kathawala 2001). Furthermore, coalitions may disagree with regard to administrative issues, such as problem solving routines, supervisory and control policies, and prioritization of tasks due to different organizational cultures (Li and Hambrick 2005). Hence, process conflicts are also likely to arise between the coalitions in joint teams.

A demographic divide splits a group into subgroups based on the alignment of subgroup members’ demographic characteristics (Lau and Murnighan 1998). It is based on easily detectable and relatively stable individual characteristics, such as age, gender, and educational background (Flache and Mäs 2008). The more attributes are highly correlated, the stronger the demographic divide. In contrast to a pre-established organizational divide, a demographic divide often arises accidentally due to functional staffing decisions (Li and Hambrick 2005). Since demographic attributes are easily observable, even for group members who do not know each other well, subgroups based on demographic characteristics may form at the beginning of the group development process and influence subsequent processes (Lau and Murnighan 1998). In contrast to an organizational divide, a strong demographic divide results in homogenous subgroups in which members share a number of demographic characteristics (Bezrukova et al. 2009). Therefore, each subgroup based on a strong demographic divide forms a cohort of people "who share a similar background and have a similar perspective on things" (Gibson and Vermeulen 2003, p. 203).

Unlike coalition members, cohort members do not necessarily pursue a common goal. And unlike coalitions, cohorts do not necessarily compete against each other. Therefore, goal and process conflicts are less likely to occur between cohorts. But the strong demographic divide between cohorts may induce another type of conflict which pertains to differences in viewpoints, ideas, and opinions (Jehn and Bendersky 2003). Such content-related conflicts tend to arise because cohorts encourage their members to express their unique perspectives and divergent opinions. Furthermore, subgroup formation based on demographic similarities increases relationship conflict between cohorts stemming from differences in personal taste, interpersonal style, and values (De Dreu and Weingart 2003). Relationship conflicts tend to be associated with negative affective reactions, such as stereotyping and low interpersonal liking (Van Knippenberg et al. 2004).

Overall, the conceptual differences show that each type of divide influences group performance in different and unique ways. Thus, the organizational and the demographic divide must be treated as separate concepts that may occur independently. By doing so, we diverge from previous literature (e.g., Hambrick et al. 2001, Li and Hambrick 2005) and are able to explain some of the inconsistent findings in previous studies (Van Knippenberg and Schippers 2007).

Necessary and sufficient conditions for R&D performance in diverse teams

Following a configurational methodological approach, we seek to identify necessary and sufficient conditions for R&D team performance in diverse teams. A necessary condition implies that an outcome can be attained only if the condition (or a combination of conditions) is given, while a sufficient condition denotes that a condition (or a combination of conditions) will always lead to an outcome (Fiss 2007). We draw on the information/decision making perspective (Ancona and Caldwell 1992, Earley and Mosakowski 2000, Van Knippenberg et al. 2004), research on demographic faultlines (e.g., Bezrukova et al. 2009, Lau and Murnighan 1998, 2005, Jehn and Bezrukova 2010) as well as literature on cross-categorization (Crisp et al. 2002, Phillips et al. 2004, Sawyer et al. 2006) to model as relevant conditions (1) the level of information sharing among team members, (2) the demographic divide, and (3) the organizational divide. Given that most other factors that have been shown to influence performance outcomes in past diversity research are held constant in our setting (see Horwitz and Horwitz 2007 and Joshi and Roh 2009 for recent meta-analyses), we focus on these theoretically relevant conditions of R&D performance which may separately or in conjunction influence team performance.

Information sharing

At the core of the positive effects of diversity lies the notion that diversity is associated with a broad range of knowledge, skills, and abilities that are distinct and non-redundant (Van Knippenberg et al. 2004). However, the mere existence of diverse knowledge does not increase R&D team performance. Rather, the group-level exchange and elaboration of diverse information and perspectives are critical (Phillips et al. 2004). Especially in novel and explorative tasks like research and development, information sharing is essential (Jackson et al. 2003, Lewis 2004, March 1991). Innovation is based on knowledge creation and knowledge integration (Leiponen 2006). Sharing information allows group members to bring unique knowledge or ideas to the interaction (Paulus 2000). Furthermore, information exchange facilitates the transformation of unique knowledge into group knowledge (Amabile et al. 2001, Bstieler and Hemmert 2010). Through intensive communication, R&D teams develop a shared language (Katz and Allen 1982, March 1991) and a common understanding about proposed solutions (Gibson and Vermeulen 2003). Increased levels of information sharing enhance integrated problem solving and improve research outcomes (Lawson et al. 2009). Thus, we consider a high level of information sharing a prerequisite or necessary condition for R&D success.

Previous research suggests that when a group divide is strong, information sharing occurs within rather than across subgroups (Lau and Murnighan 2005). Hence, group divides and information sharing may be correlated but a strong group divide does not determine a high level of information sharing among project team members. First, information sharing may be encouraged by organizational routines such as weekly meetings, structured technology fairs, or formal requests for information (Lawson et al. 2009) or simply enforced by pressing deadlines (Lau and Murnighan 1998). Second, in a cohesive subgroup, members may exchange less rather than more information, due to a high pressure to conform (Janis 1982) or because members may overestimate similarities with in-group members with regard to opinions and knowledge (Rockeach 1960). As a result, the effect of diversity on communication processes remains ambiguous (Jackson and Joshi 2011). We therefore consider information sharing a factor that may influence team performance separately from the demographic divide. Since information sharing is considered a prerequisite for team success on novel tasks, we speculate that it is a necessary condition for R&D team performance.

The notion of information sharing as a necessary condition for R&D success is not trivial for two reasons. First, intensive information sharing is time-consuming and may even impede routine tasks for which employees can rely on existing knowledge (Hansen et al. 2001). However, in novel and explorative tasks, like research and development, it is essential. Second, the hypothesis implies that for high R&D performance, it is not sufficient. Research teams may share information intensively, but unless other conditions are met, their performance may remain poor.

HYPOTHESIS 1 (H1). *Intensive group-level information sharing is necessary to achieve high R&D team performance.*

Demographic divide

In groups with a strong demographic divide, members will differentiate themselves and others as belonging to specific subgroups. Social identity theory (e.g., Hogg 1992, Tajfel 1982) suggests that the categorization of self and others into in-group and out-group affects self-perception and conduct as well as the perception and evaluation of others (Bezrukova et al. 2009, Homan et al. 2007). Demographic characteristics constitute the most salient bases upon which individuals classify themselves and others into subgroups (Ibarra 1992, Tajfel and Turner 1986). These individual attributes which are fixed or change slowly influence subgroup formation. We argue that, under certain conditions, subgroups based on a demographic divide may enable the group to reap the benefits of diversity because these subgroups constitute a supportive cohort. Cohort members perceive each other as similar. Research provides abundant evidence that demographic similarity predicts frequency and quality of interaction (e.g., Brass 1985, Ibarra 1992, McPherson et al. 2001) and friendship formation in workgroups (e.g., Gibbons and Olk 2003, Mehra et al. 1998).

The beneficial effects of a demographic divide stem from a number of mechanisms. According to the homophily principle (Byrne 1971, McPherson et al. 2001) perceived similarity breeds liking and familiarity. Group members tend to seek support and validation of their knowledge from one another (Festinger 1954), and collaborative innovation requires team members to feel psychologically safe (Bstieler and Hemmert 2010). Early studies by Asch (1956) reveal that a person is more likely to express an opinion when there is at least one other who is expected to provide support. Thus, subgroups based on a demographic divide may "neutralize the fear of embarrassment" (Edmondson et al. 2001). In homogenous cohorts, members are more apt to express new ideas and divergent perspectives, because friendship and familiarity reduces anxiety, increases self-efficacy, and promotes trust among cohort members (Bezrukova et al. 2010, Earley and Mosakowski 2000, Phillips et al. 2004). Furthermore, demographic similarity increases solidarity and helping among cohort members (Van der Vegt et al. 2006). As a consequence, the presence of similar others enhances both the quantity and the quality of the input provided by a member (Swann et al. 2004, Zarnoth and Sniezek 1997). Furthermore, homogeneity among team members facilitates knowledge integration (Katz and Allen 1982, O'Reilly et al. 1989, Smith et al. 1994). Gibson and Vermeulen (2003, p. 203) conclude that, “without a cohort, unique insights do not surface or are not taken into account by the rest of the team”. Thus, subgroups based on a demographic divide may increase creativity and innovative performance of teams.

However, much research on group faultlines suggests that cohort formation leads to performance losses due to polarization and group conflicts (e.g., Bezrukova et al. 2009, Lau and Murnighan 1998, Lau and Murnighan 2005). According to social identity theory, individuals who identify with a subgroup tend to achieve and maintain in-group/out-group comparisons that favor the in-group over the out-group (Klein et al. 2004, Mehra et al. 1998, Tajfel and Turner 1986). Perceived and pronounced demographic dissimilarities are expected to foster dislike of out-group members. Furthermore, in-group favoritism may lead to strong and polarized subgroup positions (Isenberg 1986, Lau and Murnighan 1998, Lau and Murnighan 2005). Yet, empirical findings are mixed. For example, Bezrukova et al. (2009) provide evidence that a demographic divide in workgroups of a Fortune 500 organization is negatively related to group performance. But Lau and Murnighan (2005), studying faultlines based on gender and ethnicity in student groups, do not find a negative impact of a demographic divide on expected group performance. Findings by Gibson and Vermeulen (2003) and Thatcher et al. (2003) indicate that groups with medium faultline scores show the highest level of performance and the lowest level of conflict. Taking a closer look, we argue that intensive information sharing may countervail conflicts triggered by demographic divides.

Between cohorts, content-related conflicts are likely to occur. Although conflict about perspectives and opinions is shown to increase creativity in groups (De Dreu 2006, Jehn and Mannix 2001) it may hurt implementation by limiting consensus (Amason 1996). Due to in-group favoritism, information from dissimilar others may be considered less influential or even be rejected (Flache and Mäs 2008, Lau and

Murnighan 1998). Thus, for a constructive content-related conflict to enhance group performance, strong information sharing across subgroups needs to enable the group to reach consensus and to increase subsequent commitment to implementing group decisions. In groups that support a constructive debate through intensive information sharing, content-related conflicts can be healthy (Jehn 1995, 1997). Furthermore, high levels of information sharing may also mitigate relationship conflicts which are shown to hamper group performance and creativity (Jehn and Bendersky 2003). Information from non-cohort members may override stereotype-based biases and make demographic differences less salient (De Dreu 2006, Harrison et al. 1998, Nelson 1989).

High levels of information sharing between subgroups do not only reduce potential conflicts but also enhance collective team identification and team learning. As Van der Vegt and Bunderson (2006) show, benefits of team diversity are realized through team learning efforts which are positively influenced by the interaction between diversity and team identification. Therefore, for a research team to be successful, the existence of demographic subgroups that serve as supportive cohorts for their members is likely to be insufficient for overall group performance. Rather, teams must realize the potential benefits from supportive cohorts through team learning while avoiding disruptive conflicts that may be associated with a strong demographic divide. If research teams maintain an open exchange of information despite the emergence of salient subgroups, they are able to reap the benefits of a strong demographic divide without taking performance losses. Thus, we conclude that teams achieve R&D success if they exhibit a strong demographic divide in combination with a high level of information sharing.

HYPOTHESIS 2 (H2). *A demographic divide combined with intensive information sharing on the group level is sufficient to achieve superior R&D team performance.*

The second hypothesis implies that R&D performance is high if teams show a demographic divide in combination with high levels of information sharing. However, based on the concept of equifinality, we assume that teams with other combinations of conditions can achieve R&D success as well.

Organizational divides and cross-cutting demographic divides

Although joint teams face more challenges than unilateral teams, they have a unique capacity for innovation (Bstieler 2006, Du Chatenier et al. 2009, Lawson et al. 2009). Drawing on resources, experiences, and processes from different organizations surpasses the heterogeneity derived from individual differences. However, in order to unleash the potential of joint R&D teams, additional conditions must be fulfilled.

Joint research teams consist of coalitions. In contrast to cohorts based on a demographic divide, coalition members do not necessarily contribute unique knowledge. In coalitions in which members pursue a common goal in competition with other coalitions, coalition members may refrain from putting forward new ideas and divergent opinions. Coalitions are expected to strive for unanimity and try to reconcile differences in order to take action as a coalition (Stevenson et al. 1985). This pressure to conformity is likely to reduce creativity (West 2002). Furthermore, coalition members are likely to be demographically different, such that cohesion based on homophily is unlikely to occur. Individuals do not necessarily perceive their coalition members as supportive and understanding. Thus, while cohorts encourage members to express unique insights, coalitions may even hamper the generation of innovative ideas on the subgroup level.

As coalitions in a team pursue different goals and compete with one another over resources, they tend to engage in goal and process conflicts. These types of conflicts are shown to hamper group performance (Jehn and Mannix 2001) and are expected to reduce creativity, “as group members claim or blame others for ideas” (Jehn and Bendersky 2003, p. 210). Because conflicts induced by organizational divides are different in kind and may be more severe than content-related or relationship conflicts induced by demographic divides (Li and Hambrick 2005), intensive level of information sharing across coalitions may not be sufficient to overcome goal conflicts and competitive relationships. As Lau and Murnighan (1998) show, cross-subgroup interactions do not always improve group outcomes. Hence, we argue that, in addition to high levels of information sharing, it takes a demographic divide which cuts across a pre-established, organizational divide to mitigate problems that typically occur in joint teams.

Li and Hambrick (2005) provide evidence that group performance suffers even more when coalitions based on pre-established faultlines also differ distinctly in their demographic characteristics. In other words, when organizational and demographic schisms are congruent, process losses and conflicts are exacerbated. Yet, the pre-established divide and the demographic divide do not necessarily overlap. On the contrary, since they come about for different reasons and independently, a cross-cutting of the organizational and the demographic divide will be the rule rather than the exception.

If the two divides cut across each other, the cohort and the coalition to which any member belongs are not identical. Then, team members identify with different subgroups at the same time. Accordingly, others can be cross-categorized, i. e. they are simultaneously classified as in-group and out-group members, depending on the salient categorization criterion (Brewer 2000, Hewstone et al. 2002). In joint teams, the demographic divide provides the opportunity to cross-categorize team members (Crisp et al. 2002). If the demographic divide cuts across organizational boundaries, a team member who represents a different organization may at the same time be considered as an in-group member due to demographic similarities. Cross-categorization emphasizes similarities across subgroups (Brewer 2000, Bezrukova et al. 2009). Hence, organizational boundaries become less salient, conflicts less intensive, and interactions between coalitions more productive (Crisp and Hewstone 2000). Similarly, relationship conflicts between cohorts of similar others are less likely because members of different demographic subgroups may represent the same organization and thus pursue common interests. Small group experiments provide evidence for a positive effect of crosscut groups on group performance (e.g., Phillips et al. 2004, Sawyer et al. 2006). In line with our arguments, Thatcher et al. (2003) attributed their findings that groups with medium faultlines experienced fewer conflicts and better team performance to overlapping group memberships.

Again, in order for crosscutting organizational and demographic divide to translate into superior R&D performance, intensive information sharing across subgroups is critical. The benefits of crosscutting group splits are expected to materialize only if joint groups manage to integrate diverse viewpoints, ideas, and perspectives and to converge to on implementable solution through intensive communication on the group level.

HYPOTHESIS 3 (H3). *Joint R&D teams achieve high R&D performance only if they show a strong demographic divide that cuts across organizational boundaries in combination with a high level of information sharing.*

Method

Research site

The hypotheses were tested in the context of a single R&D partnership between a university and a large company in Germany. The partnership organizes R&D projects in information and communication technology, ranging from applied research (such as product development) to more basic research. Some projects are conducted by a team of university or company employees, other projects are truly interorganizational, conducted by employees from both the university and the company. The partnership is a long-term arrangement and has existed since the mid 1980's.

This setting has two key advantages. First, by studying teams in one partnership, we control for a whole range of factors that may influence the performance of diverse teams (Du Chatenier et al. 2009, Horwitz and Horwitz 2007, Joshi and Roh 2009). In particular, national culture, organizational culture, location, and governance mechanisms as well as team type, task interdependence, task complexity, and occupational demography can all be assumed as identical for the purpose of this study, thus allowing us to focus on the impact of team composition. Second, our study diverges from previous research on divides in joint teams (Li and Hambrick 2005, Hambrick et al. 2001), because rather than focusing on joint teams only, the setting allows us to compare R&D performance in joint and unilateral teams. This is because in the partnership both joint and unilateral teams work on similar projects.

Data were collected from archives and an online questionnaire survey. From archival data of the partnership, its various projects were identified and information on team composition in each project was retrieved. Only projects were considered that involved at least three (and up to ten) researchers and were launched between 1996 and 2008. Overall, 55 projects were identified. All leaders of those projects were contacted in 2009 and directed to an online questionnaire, which covered an assessment of the project teams' behavior and performance. Questionnaires were completed for 51 projects.

Overall, data for 21 joint teams and 30 unilateral teams were available for analysis. A total of 238 employees were involved in the projects. Average age among employees was at 34 years, 23 percent of employees were female, 67 percent of employees had a degree in information science, and 32 percent held a PhD.

Measures

R&D team performance. In accordance with a number of studies on team's innovative performance (e.g., Ancona and Caldwell 1992, Eisenbeiss et al. 2008, Katz and Allen 1982), our methodology for measuring team performance was based on the project leader's evaluation. The project leaders were asked to assess team performance based on nine items (each measured on a five-point scale) developed by a consortium of German research associations. This measure was used to accommodate the specifics of our sample, i.e., R&D teams operating under the auspices of a university-industry research partnership. As for example in Reagans and Zuckerman (2001), the construct is conceived as a combination of several defining characteristics of R&D team performance which are considered formative indicators (Diamantopoulos and Siguaw 2006). Each indicator was related to a different aspect of the project's performance: commercial profit, scientific benefit, contribution to a new product, contribution to the improvement of a product, contribution to a new process, contribution to the improvement of an existing process, realized industrial application of the results, realized industrial application of the results by way of further R&D. These items were all found to be positively and significantly correlated with the global item "overall R&D success" (p<0.01). Although internal consistency is not considered relevant under the formative measurement perspective (Bollen and Lennox 1991), Cronbach's alpha for this measure was .83, indicating that project leaders usually considered the project either successful or unsuccessful on all characteristics. We used the mean of the scores in all nine items. In nine of the projects, two project leaders were involved. We asked both leaders for their evaluation and averaged the score. Mean performance for the projects was at 3.1, with a standard deviation of .69.

Information sharing. The degree of information sharing was based on the project leader's retrospective evaluation of the team. An established three-item scale was used (Zellmer-Bruhn et al. 2008). The project leaders were asked to report their agreement on a five-point scale on three statements: "Members of my team were very willing to share information with each other about our projects"; "There is a frequent exchange of information in our team"; "In our team, members engage in open communication". Cronbach's alpha was .94, and the average variance extracted, as derived from confirmatory factor analysis, was .89. The mean of the scores were used, and the scores were averaged if two leaders were involved. Information sharing ranged from 1 to 5 with a mean of 3.69 and a standard deviation of .90.

Demographic divide. The degree of demographic divide was measured as "faultline strength". We measured the demographic divide by combining demographic characteristics (age, gender, level of education, and branch of academic study). All these attributes are easily observable and have been shown to serve as salient bases for social categorization processes in work groups (Van Knippenberg et al. 2004). The stronger the alignment of the demographic characteristics, the clearer is the basis for differentiation between subgroups (Lau and Murnighan 1998). Following Flache and Mäs (2008) and Thatcher et al. (2003), we integrated all attributes in one index rather than calculating several indices referring to different attribute types. Meta-analyses by Horwitz and Horwitz (2007) and Webber and Donahue (2001) lend support to this approach by showing that the distinction between highly job-related attributes and less job-related attributes is not associated with differential relationships with group performance.

We used the algorithm developed by Thatcher et al. (2003) and applied in other faultline studies (e.g., Bezrukova et al. 2009, Lau and Murnighan 2005, Molleman 2005) to compute faultline strength. Variation in the demographic characteristics between two subgroups is defined as a ratio: the sum of the squared differences of the subgroup mean from the total mean of the characteristics divided by the total sum of the squared individual differences to the overall mean of the characteristic. This relative variation – subgroup sum of squares to total sum of squares – is computed for all possible splits of the team into two subgroups. For n team members, there are 2^{n-1}-1 possible splits into two groups. Faultline strength is defined as the maximum relative variation over all possible splits. Faultline strength, and hence demographic divide, may vary between 0 and 1, with 1 indicating the strongest possible divide. In the sample, scores of the demographic divides ranged from .35 to 1 with a mean of .70.

Organizational divide. In the sample, there were 21 joint teams, that is, they were composed of members both of the university and the company. Rather than measuring the organizational divide as a dichotomous measure, we constructed an index for the degree of organizational divide by applying Blau's (1977) heterogeneity index *H*. If *p* is the share of university members in the R&D team, then *H* is defined as $H = 1 - 2p^2$. *H* can take on values from 0 (no diversity) to .5 (maximum diversity). In the sample, organizational divide ranged from 0 to .5 with a mean of .17. By inspecting the cases individually, we found that demographic divides cut across organizational divides for all the teams in our sample. In other words, subgroups based on demographic divides are incongruent with subgroups derived from organizational divides. Thus, the sample does not include teams with a potentially negative overlap of demographic and organizational divides, but the data allow us to test the hypothesized positive effect of crosscutting divides.

Descriptive statistics and correlations for our data are provided in Table 1.

Table 1 Means, Standard Deviations, and Correlations (p values in parentheses)

	Mean	s.d.	1	2	3
1. R&D team performance	3.10	0.69			
2. Information sharing	3.69	0.90	0.34 (0.02)		
3. Organizational divide	0.17	0.22	-0.23 (0.10)	-0.13 (0.36)	
4. Demographic divide	0.70	0.19	0.30 (0.03)	0.22 (0.12)	-0.38 (0.01)

Data analysis

We examined the data applying fuzzy-set qualitative comparative analysis (fsQCA). FsQCA was introduced by Ragin (2000) as a method to analyze complex causality. While qualitative comparative analysis is becoming increasingly popular in organization and management science (e.g., Fiss in press, Grandori and Furnari 2008, Greckhamer et al. 2008, Kogut et al. 2004, Schneider et al. 2009), it has rarely been applied to explain group level outcomes (see for one exception Bakker et al. in press).

In fsQCA, an observation or case is described by a combination of "causal conditions" and the "outcome". Causal links are expressed in set-theoretic language. All raw data are first calibrated into set membership values ranging from 0 (the observation is fully out of the set) to 1 (the observation is fully in the set). Based on the membership values, fsQCA then implements algorithms that explore how the membership of cases in causal conditions is linked to membership in the outcome. Causal links are established as necessary and sufficient conditions, and both individual causal conditions and combinations of conditions may be found to be linked to the outcome.

FsQCA differs in important ways from regression analysis (Mahoney and Goertz 2006, Pajunen 2008). For our analyses, fsQCA seemed more appropriate for three reasons. First, fsQCA is aimed at detecting complex causal links termed "multiple conjunctural causation" (Rihoux 2006). "Conjunctural" causation refers to the idea that combinations of conditions, rather than one condition alone, is related to an outcome. “Multiple” causation or equifinality refers to the idea that more than one of those combinations of conditions may serve as a causal path to an outcome. Our hypotheses imply that the causal links may be complex, as defined here. In particular, we speculated that joint R&D teams will perform well if members share information intensively and the demographic divide is strong (conjunctural causation). But we also stated that unilateral teams may be similarly successfully (equifinality). Such complex interactions are difficult to model in regression analysis.

Second, fsQCA expresses causal links as necessary and sufficient conditions and is thus the adequate method to test our hypotheses. For example, we stated that high levels of information sharing will be necessary to achieve high R&D team performance. We further conjectured that different causal paths, some involving joint teams, some unilateral teams, may be sufficient to achieve strong R&D team performance. Regression analysis allows testing marginal effects but is not suitable for identifying necessary and sufficient conditions. From findings on hypotheses about necessary and sufficient conditions, clearer policy implications may be derived than from marginal effects of regression analyses (Fiss 2007).

Finally, fsQCA follows case-study logic: Its goal is to explain the occurrence of an outcome in a particular setting among a number of cases. Such an analysis may be conducted with relatively small numbers of observations, typically starting around 10, but it rests on an intimate knowledge of underlying cases. Generalization is by theory rather than by statistical estimation to a population. Our research site fits this methodology well. Our sample is relatively small (n=51), and the idiosyncratic setting of one single partnership does not permit statistical generalization. But since we know the underlying cases well, informed interpretation of the results is possible.

Calibration and analysis

Calibration. To calibrate the raw data, three anchors need to be determined: two values of the original data that define nearly full membership and nearly full non-membership, respectively, and a crossover point at which a case is neither more in nor more out of the set (Ragin 2000). These anchors are assigned set membership values of .95, .05 and .5, respectively. Intermediate set membership values for all cases are then defined by applying the log odds method (Ragin 2008). We applied consistent rules for the outcome and the causal conditions by setting the cross-over point at or near the mid-range of the variable. Likewise, we set the .95 value near the maximum and the .05 value near the minimum of the variable (for details see Table 2).

Table 2 Calibration

	Min	Max	Mean	0.95	0.5	0.05
R&D team performance	1.00	5.00	3.10	4.30	2.95	1.60
Information sharing	1.00	5.00	3.69	4.30	2.95	1.60
Organizational divide	0.00	0.50	0.17	0.40	0.25	0.10
Demographic divide	0.35	1.00	0.70	0.95	0.70	0.45

Analysis of necessary conditions. A causal condition is called "necessary" if the instances of the outcome form a subset of the instances of the causal condition (Ragin 2006). This implies that the set membership value of the outcome Y is lower than the set membership value of the causal condition X for each case. Some cases may not meet that rule. Therefore Ragin (2006) developed a consistency measure quantifying the degree to which the observations conform to the strict rule. Let Y denote the outcome, and I, the number of cases. Then the consistency score of a necessary condition X is defined as:

$$Consistency(X_i \leq Y_i) = \frac{\sum_{i=1}^{I} \min(X_i, Y_i)}{\sum_{i=1}^{I} Y_i}.$$

A consistency score of 1 indicates that the combination of causal conditions meets the rule across all cases. The more cases fail to meet the rule for a necessary condition, and the larger the distance from meeting the rule, the lower the consistency score will be below 1. A causal condition is conventionally called "necessary" or "almost always necessary" if the consistency score exceeds the threshold of .9. We analyzed whether any of the three causal conditions, and their negations, are necessary to account for

R&D team performance. It was then tested whether the conditions found to be necessary are non-trivial. A necessary condition is trivial if it occurs in all cases independent of the presence or absence of the outcome. For example, the existence of computers to document the team's findings would be a trivially necessary condition for R&D team performance. The measure to evaluate whether a necessary condition is non-trivial is the coverage rate (Ragin 2006). Let Y again denote the outcome, and I, the number of cases. Then the coverage rate of a necessary causal condition X, or of a combination of conditions, is defined as:

$$Coverage(Y_i \leq X_i) = \frac{\sum_{i=1}^{I} \min(X_i, Y_i)}{\sum_{i=1}^{I} X_i}.$$

A trivially necessary condition would yield a coverage rate near 0.

Analysis of sufficient conditions. In order to analyze sufficient conditions, ideal types are created by converting the set membership values for the causal conditions into the crisp-set values 0 or 1. A case is assigned a value of 1 if the set membership value exceeds the fuzzy value of .5; and a value of 0, in all other cases. A causal condition can be considered sufficient to lead to the outcome if, for each case, the set membership value of the causal condition X does not exceed the set membership value of the outcome Y (Ragin 2000). The same applies for conditions joined by a logical "and", expressed as (X*Z). Since combinations of conditions rarely meet the rule for sufficiency across all cases, a consistency measure is invoked. If Y again denotes the outcome, and I the number of cases, then the consistency score of a causal condition X, or of a combination of conditions, is given by:

$$Consistency(X_i \leq Y_i) = \frac{\sum_{i=1}^{I} \min(X_i, Y_i)}{\sum_{i=1}^{I} X_i}.$$

Causal combinations of conditions exceeding an appropriate cut-off consistency score are categorized as sufficient, and the outcome is therefore assigned a value of 1 in the truth table. Conversely, causal combinations with a consistency level below or at the cut-off value are not considered sufficient, and the outcome is assigned a value of 0. Various possibilities are given to determine the cut-off value (Ragin 2005).

In a next step, the combinations of causal conditions that were found sufficient are subjected to the truth table algorithm. It compares combinations in order to reduce the number of expressions needed to describe the sufficient combinations of conditions (Ragin 2008). Usually, not all cases meet the rule for a sufficient combination of conditions. Therefore, each sufficient combination of conditions leading to a positive outcome can be described by its consistency score (see above) and by two coverage scores (Ragin 2006). If Y denotes the outcome, and I, the number of cases, then the coverage rate of a sufficient causal condition X, or of a combination of conditions, is given by:

$$Coverage(X_i \leq Y_i) = \frac{\sum_{i=1}^{I} \min(X_i, Y_i)}{\sum_{i=1}^{I} Y_i}.$$

The coverage rate provides information about the empirical importance of a combination of conditions. Raw coverage refers to the coverage of all the causal conditions. But single cases are usually explained by more than one expression. Unique coverage controls for overlapping explanations. It is calculated for a certain causal condition by subtracting the joint raw coverage of all the remaining causal paths from the joint raw coverage of all causal paths including the one of interest.

Results

Hypothesis 1

According to Hypothesis 1, intensive information sharing is a necessary condition for R&D team performance. This can be tested by analyzing necessary conditions (Table 3). We found that none of the causal conditions (nor their negations which are indicated by minor letters) achieved the conventional threshold value of .9 for the consistency score. However, information sharing had the highest consistency score with .88 and exceeded the next highest score by far (.71 for the absence of an organizational divide). Hence, intensive information sharing may be called an almost necessary condition.

Table 3 **Analysis of necessary conditions for high R&D team performance**

Causal Condition	Consistency	Coverage
ORGANIZATIONAL DIVIDE	0.32	0.49
organizational divide	0.71	0.62
DEMOGRAPHIC DIVIDE	0.67	0.79
demographic divide	0.58	0.62
INFORMATION SHARING	0.88	0.67
information sharing	0.33	0.68

Capital letters: The condition is present. Minor letters: The condition is absent.

Furthermore, information sharing was found to be a non-trivial necessary condition. The coverage rate of .67 indicates empirical importance, that is, there are cases in which information sharing is absent. Overall, therefore, there was support for Hypothesis 1: Teams usually do not achieve strong R&D performance unless they share information intensively.

Hypotheses 2 and 3

According to Hypothesis 2, high levels of information sharing and a demographic divide are sufficient to explain strong R&D team performance, whether in joint or in unilateral teams. According to Hypothesis 3 joint teams will only achieve high R&D team performance if the demographic divide is strong and is combined with high levels of information sharing. These hypotheses can be tested by analyzing sufficient conditions.

We found seven out of eight logically possible combinations of causal conditions (Table 4). The configurations I to IV can be considered as sufficient to explain a positive outcome. This is first because the consistency score drops substantially, from a value .81 to .71, when we move from configuration IV to V. The existence of a substantial gap is considered as an important rule of thumb to differentiate consistent causal combinations from inconsistent ones (Ragin 2005). As a second reason, the mean values of R&D team performance showed a similarly strong drop from IV (3.29) to V (2.62).

Table 4 Enlarged truth table for R&D team performance and three causal conditions

Configuration	Organizational divide	Demographic divide	Information sharing	R&D team performance	n	Consistency	Mean R&D
I	●	●	●	●	4	0.93	3.34
II	⊗	⊗	●	●	8	0.88	3.35
III	⊗	●	⊗	●	2	0.81	3.56
IV	⊗	●	●	●	17	0.81	3.29
V	⊗	⊗	⊗	⊗	5	0.71	2.62
VI	●	⊗	⊗	⊗	3	0.69	2.76
VII	●	⊗	●	⊗	12	0.60	2.78

n: number of observations; ●: condition is present; ⊗: condition is absent

Table 5 Sufficient combinations of conditions for high R&D team performance

Configurations (see Table 4)	Path	Reduction to causal path	Raw coverage	Unique coverage	Consistency
II, IV	1	organizational divide * INFORMATION SHARING +	0.62	0.16	0.73
I, IV	2	DEMOGRAPHIC DIVIDE * INFORMATION SHARING +	0.61	0.15	0.83
III, IV	3	DEMOGRAPHIC DIVIDE * organizational divide	0.52	0.05	0.77

*Consistency cutoff: 0.81; the complex solution is reported. Capital letters: The condition is present. Minor letters: The condition is absent. *: logical “and”. +: logical “or”.*

The truth table algorithm produces a solution that minimizes the expressions needed to describe all sufficient combinations of conditions (Table 5). The new, logically minimized expressions are derived by reducing the combinations in the truth table (Table 4). The algorithm arrived at three expressions or causal paths that are sufficient conditions for a positive outcome. Path 1 combines the absence of an organizational divide with information sharing; path 2 combines a demographic divide with information sharing; and path 3 combines a demographic divide with the absence of an organizational divide.

The findings support Hypothesis 2. As path 2 in Table 5 shows, a demographic divide with information sharing sufficiently explains strong R&D team performance. This path is followed by the four cases of configuration I and the 17 cases of configuration IV. For this path, an organizational divide is not relevant in accounting for a positive outcome. Configuration I refers to joint teams (an organizational divide is present) but configuration IV encompasses unilateral teams.

The findings also support Hypothesis 3. All successful teams with an organizational divide (joint teams) follow path 2. This implies that an organizational divide needs to be combined with a demographic divide to sufficiently explain a positive outcome. Note that some unilateral teams do achieve a positive outcome in the absence of a demographic divide. This is evident from path 1, which summarizes configurations II and IV.

Further evidence comes from inspecting the cases in the truth table (Table 4). The four teams in configuration I are the only successful joint teams. Here, the demographic divide cuts across the organizational divide, that is, the split in the team marked by the demographic divide was not identical with organizational borders. This is in line with our speculation that the demographic divide may alleviate the problems resulting from the organizational divide. Furthermore, we compared configuration I with VI. Both are joint teams with information sharing. However, in configuration I the demographic divide is present, whereas in VI it is absent. The two combinations differ markedly in their performance. While configuration I attains the highest consistency score among all combinations, VI attains the lowest. Furthermore, average R&D team performance differs substantially between I and VI in a statistically significant way: 3.34 compared to 2.78, equivalent to a distance of .8 standard deviations. Hence, in configuration I but not in configuration VI can the potential of joint teams be transformed into strong R&D team performance because the problems of the organizational divide are overcome by a strong demographic divide.

The performance differences between the successful and the unsuccessful teams are of a considerable effect size. R&D team performance is at an average 3.33 for the successful teams and at an average 2.74 for the unsuccessful teams. Given a standard deviation of .69 the difference amounts to .85 standard deviations. The difference in mean between successful and unsuccessful groups is statistically significant ($p=.002$).

Two observations were not consistent with our predictions. The teams of configuration III showed high performance although information sharing was low. When examining the two observations, we found an explanation for this anomaly. Both teams worked on a follow-up of a previous project. Because team members knew each other well and had collaborated on a similar problem before, information sharing was not crucial for the teams to perform. In our theoretical framework, we abstracted from previous experience with an identical team on similar projects and implicitly assumed newly composed teams. This inconsistent finding further supports the notion that information sharing is not a trivial condition. Given that information sharing is time-consuming and distracts team members from other tasks, well-rehearsed teams may perform well if common knowledge and experience as well as familiarity allow them to refrain from exchanging knowledge intensively. However, in R&D teams this will be an exception rather than a rule. If we eliminated these two particular cases of follow-up project teams, the analysis would identify information sharing as a truly necessary condition, thus providing full support of Hypothesis 1. Hence, in interpreting high levels of information sharing as a necessary condition we refer to the common case of newly composed R&D teams.

We did not observe one logically possible configuration of conditions. It combines an organizational divide with a demographic divide. But because high levels of information sharing – the necessary condition – is absent, we would predict such teams to perform poorly, as implied in Hypothesis 1. Hence, observing this configuration would presumably not alter findings concerning Hypothesis 1, and it would definitely not alter our substantive findings concerning Hypotheses 2 and 3.

Additional analysis: R&D failure as outcome

In configurational thinking, explaining an outcome needs not be the mirror image of explaining the negation of an outcome. Therefore, explaining the negation of the outcome may yield additional insights. We repeated our analysis for low R&D team performance as the outcome.

Table 6 Analysis of necessary conditions for low R&D performance

Causal Condition	Consistency	Coverage
ORGANIZATIONAL DIVIDE	0.46	0.55
organizational divide	0.58	0.40
DEMOGRAPHIC DIVIDE	0.55	0.51
demographic divide	0.78	0.65
INFORMATION SHARING	0.81	0.48
information sharing	0.46	0.75

Capital letters: The condition is present. Minor letters: The condition is absent.

In the analysis of necessary conditions, neither of the conditions nor their negations were found to be necessary (Table 6). In the analysis of sufficient conditions, three configurations covering 17 observations were found to be sufficient to account for low performance: the configurations V, VI, and VII which reduce to two minimized expressions (Table 7).

Table 7 Sufficient combinations of conditions for low R&D team performance

Configurations (see Table 4)	Path	Reduction to causal path	Raw coverage	Unique coverage	Consistency
V, VI	1	demographic divide * information sharing +	0.39	0.19	0.84
VI, VII	2	ORGANIZATIONAL DIVIDE * demographic divide	0.43	0.23	0.71

*Consistency cutoff: 0.78; the complex solution is reported. Capital letters: The condition is present. Minor letters: The condition is absent. *: logical "and". +: logical "or".*

The result does not offer new insights but further corroborates our earlier findings. Two of the non-performing types are teams without information sharing (V and VI). In the other non-performing configuration (VII) information sharing is high. Thus, though intensive information sharing appears to be necessary for R&D success, information sharing alone does not ensure superior R&D performance. Hence, the findings confirm Hypothesis 1. The complex solution for low R&D performance provides further support for Hypothesis 3. As path 2 shows, teams that possess an organizational divide but no demographic divide perform poorly, regardless of whether they share information intensively or not. Thus, a crosscutting demographic divide is required to overcome the drawbacks of joint teams. In sum, analyzing poor R&D performance as outcome further strengthens our previous findings.

Discussion

The purpose of this research was to examine the effect of subgroup formation induced by group divides on R&D performance in both joint and unilateral research teams. Based on a configurational approach (Fiss 2007) we demonstrated that (1) intensive information sharing is a necessary condition for high R&D team performance, (2) teams with a demographic divide perform well when information sharing is high, and (3) joint teams only achieve R&D success when information sharing is high and a demographic divide cuts across the organizational boundaries.

Our analysis contributes to the scarce literature on how to facilitate success in joint R&D teams (Bstieler and Hemmert 2010, Hoang and Rothaermel 2005). Though some studies have discussed subgroup formation in the context of interorganizational teams (Li and Hambrick 2005), we showed for the first time for R&D teams that a crosscutting demographic divide may offset the disadvantages posed by joint teams. In light of our results, it is not surprising that previous findings regarding the performance of joint research teams were ambiguous (Du Chatenier et al. 2009, Milliken and Martins 1996). In our sample, some joint teams were highly successful, while others performed poorly. The combination of two conditions differentiates the successful from the unsuccessful joint teams: a crosscutting demographic divide and high levels of information sharing.

Our study also has two implications for research on group faultlines. First, adding to the approach by Bezrukova et al. (2009) and Li and Hambrick (2005) who suggest that group splits may differ in nature, we provide evidence that organizational divides and demographic divides are linked differently to group performance. While a pre-established organizational divide entails the formation of coalitions which compete against each other over resources and pursue divergent interests, a demographic divide leads to homogenous subgroups which serve as supportive cohorts for their members. Second, we provide one of the first empirical examinations of the effect of crosscutting divides in actual R&D teams. Our results suggest that fighting an organizational faultline with a crosscutting demographic divide shows great promise for joint R&D teams. Furthermore, we provide empirical evidence that the curvilinear effect of group faultlines on group performance, as reported by Gibson and Vermeulen (2003) and Thatcher et al. (2003) may be attributed to crosscutting divides rather than medium faultline strength, as conjectured by Thatcher et al. (2003) and Van Knippenberg and Schippers (2007).

Another contribution this paper makes to existing research on group composition and team performance is methodological. By applying fsQCA, we were able to identify complex causal links that lead to superior R&D performance. In particular, fsQCA provides two insights that help explain previously inconsistent findings concerning the effect of group faultlines on performance attained by regression analysis. First, we observe teams with a strong demographic divide that achieve R&D success as well as successful teams that lack a demographic divide. The same applies to teams with an organizational divide. As a consequence, in regression analysis, we did not find a significant effect of either type of divide with R&D performance (results not reported here). However, it would be wrong to conclude that subgroup formation is irrelevant for R&D performance, as our findings show. Second, as fsQCA accounts for equifinality, we were able to uncover multiple paths to R&D success. For example, teams with a strong demographic divide are equally successful as teams without a demographic divide, as long as both share information intensively and do not hold an organizational divide. These findings would not have been obtained using regression analysis. In sum, applying fsQCA rather than regression analysis may be an interesting option for those who study links between team composition and performance, especially if samples are small, still the conjectured links are complex, and the research is usually idiosyncratic rather than representative for large sections of an economy. Under these circumstances, fsQCA has advantages, as our study illustrated. Furthermore, the idea of multiple conjunctural causation, included in fsQCA, allows better formulation of policy and managerial implications than regression analysis.

Limitations and future research

Our study has several limitations that invite future research. While the special empirical context we studied has several advantages, it does not allow generalization in a statistical sense. We looked at one research partnership involving a German company and a German university in one particular field of study, information and communication technology which allowed us to study both joint and unilateral teams and to control for a variety of factors that may influence R&D team performance beyond group composition. However, it remains open whether our findings can be generalized to other settings. Future studies on the effect of crosscutting divides are certainly warranted for other joint teams, such as cross-cultural teams, joint venture teams, or merger integration teams (Bouncken and Winkler 2010, Hambrick et al. 2001).

In combining archival data with perceptual evaluations of R&D team performance by the project team leaders, we were able to reduce common method bias (Podsakoff et al. 2003). Though in our context more objective measures for all types of projects were not available, future studies may also include objective performance measures, such as adherence to budgets and time constraints, as well as team climate and satisfaction as rated by team members.

Our findings invite future research on organizational demography and the effect of divides in work groups. We have focused on surface-level characteristics as salient categories on which subgroups are formed. A number of studies provide evidence that cohesive subgroups tend to occur among demographically similar individuals (e.g., McPherson et al. 2001, Lincoln and Miller 1979, Reagans et al. 2004). However, over time, team members may also use deep-level characteristics such as attitudes, values, and personality to differentiate between in-group and out-group members (Harrison et al. 1998). An interesting topic to address in future studies is how organizational divides, demographic divides, and divides based on deep-level attributes interrelate and influence team performance over time (Phillips and Loyd 2006).

Another avenue for future research is to explore empirically the group processes underlying the effects of demographic and organizational divides on R&D performance. In particular, future studies should investigate how group divides translate into social network formation among group members. Analyzing task-related and affective network ties would uncover how subgroups based on demographic similarity or organizational affiliation affect member interaction (Van Knippenberg and Schippers 2007).

Managerial implications

Important managerial implications can be drawn from the study. Information sharing was identified as a necessary condition. The results of our empirical test show that a strong demographic divide in combination with information sharing positively influences R&D success in joint teams. However, previous research suggests that team members have a higher propensity to share information with in-group rather than out-group members (Burt 1997, Lau and Murnighan 2005). Thus, project leaders should establish information sharing routines, such as regular meetings, in order to increase information sharing across the different subgroups.

Perhaps the most important managerial implication relates to demographic team composition. Our study indicated that joint teams should be composed such that a demographic divide cuts across organizational boundaries. In an existing partnership that may be easier to achieve than in the process of partner selection. In partner selection, the demographic characteristics of the employees should become a key criterion for selecting partners, at least for important R&D projects (Hitt et al. 2000, Albanese 1994). In general, companies that plan to collaborate in R&D should not only pay attention to partnership issues on the company level but are well advised to carefully compose the individual R&D teams.

In contrast to previous research on group faultlines (e.g., Lau and Murnighan 1998, 2005, Li and Hambrick 2005, Polzer et al. 2006), our findings suggest that managers may take a more optimistic view on demographic divides. They may meliorate the performance of joint R&D teams.

References

Albanese, R. 1994. Team-building process: Key to better project results. *J. Management Eng.* **10** 36–44.

Amabile, T. M., C. Patterson, J. Mueller, T. Wojcik, P. W. Odomirok, M. Marsh, S. J. Kramer. 2001. Academic-practitioner collaboration in management research: A case of cross-profession collaboration. *Acad. Management J.* **44** 418–431.

Amason, A. 1996. Distinguishing effects of functional and dysfunctional conflict on strategic decision making: Resolving a paradox for top management teams. *Acad. Management J.* **39** 123–148.

Ancona, D. G., D. F. Caldwell. 1992. Demography and design: Predictors of new product team performance. *Organ. Sci.* **3** 321–341.

Asch, S. 1956. Studies of independence and conformity: A minority of one against a unanimous majority. *Psychological Monographs* **70** 1-70.

Bakker, R. M., B. Cambré, L. Korlaar, J. Raab. in press. Managing the project learning paradox: A set-theoretic approach toward project knowledge transfer. *Internat. J. Project Management*.

Bezrukova, K., K. A. Jehn, E. L. Zanutto, S. M. B. Thatcher. 2009. Do workgroup faultlines help or hurt? A moderated model of faultlines, team identification, and group performance. *Organ. Sci.* **20** 35–50.

Bezrukova, K., C. S. Spell, J. L. Perry. 2010. Violent splits or healthy divides? Coping with injustice through faultlines. *Personnel Psych.* **63** 719–751.

Blau, P. M. 1977. *Inequality and Heterogeneity*. *A Primitive Theory of Social Structure.* Free Pr., New York.

Bollen, K. A., R. Lennox. 1991. Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin* **110** 305–314.

Bouncken, R. B., V. A. Winkler. 2010. National and cultural diversity in transnational innovation teams. *Technology Analysis & Strategic Management* **22** 133–151.

Brass, D. J. 1985. Men's and women's networks: A study of interaction patterns and influence in an organization. *Acad. Management J.* **28** 327–343.

Brewer, M. B. 2000. Reducing prejudice through cross-categorization: Effects of multiple social identities. S. Oskamp, ed. *Reducing Prejudice and Discrimination*. *The Claremont Symposium on Applied Social Psychology*. Erlbaum, Mahwah, NJ, 165–183.

Bstieler, L. 2006. Trust formation in collaborative new product development. *J. Product Innovation Management* **23** 56–72.

Bstieler, L., M. Hemmert. 2010. Increasing learning and time efficiency in interorganizational new product development teams. *J. Product Innovation Management* **27** 485–499.

Burt, R. S. 1997. The contingent value of social capital. *Admin. Sci. Quart.* **42** 339–365.

Byrne, D. 1971. *The Attraction Paradigm.* Acad. Press, New York.

Chesbrough, H. W. 2003. The era of open innovation. *MIT Sloan Management Rev.* **44** 35–41.

Crisp, R. J., N. Ensari, M. Hewstone, N. Miller. 2002. A dual-route model of crossed categorisation effects. *The European Review of Social Psychology* **13** 35–73.

Crisp, R. J., M. Hewstone. 2000. Crossed categorization and intergroup bias: The moderating roles of intergroup and affective context. *J. Experiment. Soc. Psych.* **36** 357–383.

De Dreu, C. K. W. 2006. When too little or too much hurts: Evidence for a curvilinear relationship between task conflict and innovation in teams. *J. Management* **32** 83–107.

De Dreu, C. K. W., L. R. Weingart. 2003. Task versus relationship conflict, team performance, and team member satisfaction. A meta-analysis. *J. Appl. Psych.* **88** 741–749.

Diamantopoulos, A., J. A. Siguaw. 2006. Formative vs. reflective indicators in organizational measure development: A comparison and empirical illustration. *British J. Management* **17** 263–282.

Du Chatenier, E., J. A. Verstegen, H. J. A. Biemans, M. Mulder, O. Omta. 2009. The challenges of collaborative knowledge creation in open innovation teams. *Human Resource Development Review* **8** 350–381.

Dyer, J. H., P. Kale, H. Singh. 2004. When to ally & when to acquire. *Harvard Bus. Rev.* **82** 108–115.

Earley, P. C., E. Mosakowski. 2000. Creating hybrid team cultures: An empirical test of transnational team functioning. *Acad. Management J.* **43** 26–49.

Edmondson, A., R. Bohmer, G. Pisano. 2001. Speeding up team learning. *Harvard Bus. Rev.* **79** 125–132.

Eisenbeiss, S. A., D. Van Knippenberg, S. Boerner. 2008. Transformational leadership and team innovation: Integrating team climate principles. *J. Appl. Psych.* **93** 1438–1446.

Elmuti, D., Y. Kathawala. 2001. An overview of strategic alliances. *Management Decision* **39** 205–218.

Festinger, L. 1954. A theory of social comparison processes. *Human Relations* **7** 117–140.

Fiss, P. C. in press. Building better causal theories: A fuzzy-set approach to typologies in organization research. *Acad. Management J.*

Fiss, P. C. 2007. A set-theoretic approach to organizational configurations. *Acad. Management Rev.* **32** 1180–1198.

Flache, A., M. Mäs. 2008. How to get the timing right. A computational model of the effects of the timing of contacts on team cohesion in demographically diverse teams. *Comput. Math. Organ. Theory* **14** 23–51.

Gibbons, D., P. M. Olk. 2003. Individual and structural origins of friendship and social position among professionals. *J. Personality Soc. Psych.* **84** 340–351.

Gibson, C. B., F. Vermeulen. 2003. A healthy divide: Subgroups as a stimulus for team learning behavior. *Admin. Sci. Quart.* **48** 202–239.

Grandori, A., S. Furnari. 2008. A chemistry of organization: Combinatory analysis and design. *Organ. Stud.* **29** 459–485.

Greckhamer, T., V. F. Misangyi, H. Elms, R. Lacey. 2008. Using qualitative comparative analysis in strategic management research: An examination of combinations of industry, corporate, and business-unit effects. *Organ. Res. Methods* **11** 695–726.

Hagedoorn, J. 2002. Inter-firm R&D partnerships: An overview of major trends and patterns since 1960. *Res. Policy* **31** 477–492.

Hambrick, D. C., J. Li, K. R. Xin, A. S. Tsui. 2001. Compositional gaps and downward spirals in international joint venture management groups. *Strategic Management J.* **22** 1033–1053.

Hansen, M. T., J. M. Podolny, J. Pfeffer. 2001. So many ties, so little time: A task contingency perspective on corporate social capital in organizations. *Res. Soc. Organ.* **18** 21–57.

Harrison, D. A., K. H. Price, M. P. Bell. 1998. Beyond relational demography: Time and the effects of surface- and deep-level diversity on work group cohesion. *Acad. Management J.* **41** 96–107.

Hewstone, M., M. Rubin, H. Willis. 2002. Intergroup bias. *Annual Rev. Psych.* **53** 575–604.

Hitt, M. A., M. T. Dacin, E. Levitas, J.-L. Arregle, A. Borza. 2000. Partner selection in emerging and developed market contexts: Resource-based and organizational learning perspectives. *Acad. Management J.* **43** 449–467.

Hoang, H., F. T. Rothaermel. 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. *Acad. Management J.* **48** 332–345.

Hogg, M. A. 1992. *The social psychology of group cohesiveness. From attraction to social identity.* Harvester Wheatsheaf, New York.

Homan, A. C., D. Van Knippenberg, G. A. Van Kleef, C. K. W. De Dreu. 2007. Interacting dimensions of diversity: Cross-categorization and the functioning of diverse work groups. *Group Dynamics* **11** 79–94.

Horwitz, S. K., I. B. Horwitz. 2007. The effects of team diversity on team outcomes: A meta-analytic review of team demography. *J. Management* **33** 987–1015.

Ibarra, H. 1992. Homophily and differential returns: Sex differences in network structure and access in an advertising firm. *Admin. Sci. Quart.* **37** 422–447.

Isenberg, D. J. 1986. Group polarization: A critical review and meta-analysis. *J. Personality Soc. Psych.* **50** 1141–1151.

Jackson, S. E., M. A. Hitt, A. DeNisi. 2003. *Managing Knowledge for Sustained Competitive Advantage. Designing Strategies for Effective Human Resource Management.* Jossey-Bass, San Francisco, Calif.

Jackson, S. E., A. Joshi. 2011. Work team diversity. S. Zedeck, ed. *APA Handbook of Industrial and Organizational Psychology*. American Psychological Association, Washington DC, 651–686.

Janis, I. L. 1982. *Victims of groupthink. A psychological study of foreign-policy decisions and fiascoes.* Houghton Mifflin, Boston.

Jehn, K. A. 1995. A multimethod examination of the benefits and detriments of intragroup conflict. *Admin. Sci. Quart.* **40** 256–282.

Jehn, K. A. 1997. A qualitative analysis of conflict types and dimensions in organizational groups. *Admin. Sci. Quart.* **42** 530–557.

Jehn, K. A., C. Bendersky. 2003. Intragroup conflict in organizations: A contingency perspective on the conflict-outcome relationship. *Research in Organizational Behavior* **25** 187–243.

Jehn, K. A., K. Bezrukova. 2010. The faultline activation process and the effects of activated faultlines on coalition formation, conflict, and group outcomes. *Organ. Behav. Human Decision Processes* **112** 24–42.

Jehn, K. A., E. A. Mannix. 2001. The dynamic nature of conflict: A longitudinal study of intragroup conflict and group performance. *Acad. Management J.* **44** 238–251.

Joshi, A., H. Roh. 2009. The role of context in work team diversity research: A meta-analytic review. *Acad. Management J.* **52** 599–627.

Katz, R., T. J. Allen. 1982. Investigating the not invented here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R&D project groups. *R&D Management* **12** 7–20.

Klein, K. J., B.-C. Lim, J. L. Saltz, D. M. Mayer. 2004. How do they get there? An examination of the antecedents of centrality in team networks. *Acad. Management J.* **47** 952–963.

Kogut, B., J. P. MacDuffie, C. C. Ragin. 2004. Prototypes and strategy: Assigning causal credit using fuzzy sets. *Eur. Management Rev.* **1** 114–131.

Lau, D. C., J. K. Murnighan. 1998. Demographic diversity and faultlines: The compositional dynamics of organizational groups. *Acad. Management Rev.* **23** 325–340.

Lau, D. C., J. K. Murnighan. 2005. Interactions within groups and subgroups: The effects of demographic faultlines. *Acad. Management J.* **48** 645–659.

Lawson, B., K. J. Petersen, P. D. Cousins, R. B. Handfield. 2009. Knowledge sharing in interorganizational product development teams: The effect of formal and informal socialization mechanisms. *J. Product Innovation Management* **26** 156–172.

Leiponen, A. 2006. Managing knowledge for innovation: The case of business-to-business services. *J. Product Innovation Management* **23** 238–258.

Lewis, K. 2004. Knowledge and performance in knowledge-worker teams: A longitudinal study of transactive memory systems. *Management Sci.* **50** 1519–1533.

Li, J., D. C. Hambrick. 2005. Factional groups: A new vantage on demographic faultlines, conflict, and disintegration in work teams. *Acad. Management J.* **48** 794–813.

Lincoln, J. R., J. Miller. 1979. Work and friendship ties in organizations: A comparative analysis of relational networks. *Admin. Sci. Quart.* **24** 181–199.

Mahoney, J., G. Goertz. 2006. A tale of two cultures: Contrasting quantitative and qualitative research. *Political Analysis* **14** 227–249.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* **2** 71–87.

Marcus-Newhall, A., N. Miller, R. Holtz, M. B. Brewer. 1993. Cross-cutting category memberships with role assignment: A means of reducing intergroup bias. *British J. Soc. Psych.* **32** 125–146.

McPherson, M., L. Smith-Lovin, J. M. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Rev. Sociol.* **27** 415–444.

Mehra, A., M. Kilduff, D. J. Brass. 1998. At the margins: A distinctiveness approach to the social identity and social networks of underrepresented groups. *Acad. Management J.* **41** 441–452.

Meyer, A. D., A. S. Tsui, C. R. Hinings. 1993. Configurational approaches to organizational analysis. *Acad. Management J.* **36** 1175–1195.

Milliken, F. J., L. L. Martins. 1996. Searching for common threads: Understanding the multiple effects of diversity in organizational groups. *Acad. Management Rev.* **21** 402–433.

Molleman, E. 2005. Diversity in demographic characteristics, abilities and personality traits: Do faultlines affect team functioning? *Group Decision Negotiation* **14** 173–193.

Nelson, R. E. 1989. The strength of strong ties: Social networks and intergroup conflict in organizations. *Acad. Management J.* **32** 377–401.

Newell, S., J. Swan. 2000. Trust and inter-organizational networking. *Human Relations* **53** 1287–1328.

O'Reilly, C. A., D. F. Caldwell, W. P. Barnett. 1989. Work group demography, social integration, and turnover. *Admin. Sci. Quart.* **34** 21–37.

Pajunen, K. 2008. Institutions and inflows of foreign direct investment: A fuzzy-set analysis. *J. Int. Bus. Stud.* **39** 652–669.

Paulus, P. 2000. Groups, teams, and creativity: The creative potential of idea-generating groups. *Appl. Psychol. Int. Rev.* **49** 237–262.

Phillips, K. W., D. L. Loyd. 2006. When surface and deep-level diversity collide: The effects on dissenting group members. *Organ. Behav. Human Decision Processes* **99** 143–160.

Phillips, K. W., E. A. Mannix, M. A. Neale, D. H. Gruenfeld. 2004. Diverse groups and information sharing: The effects of congruent ties. *J. Experiment. Soc. Psych.* **40** 497–510.

Podsakoff, P. M., S. B. MacKenzie, Y.-Y. Lee, N. P. Podsakoff. 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psych.* **88** 879–903.

Polzer, J. T., C. B. Crisp, S. L. Jarvenpaa, J. W. Kim. 2006. Extending the faultline model to geographically dispersed teams: How colocated subgroups can impair group functioning. *Acad. Management J.* **49** 679–692.

Polzer, J. T., E. A. Mannix, M. A. Neale. 1998. Interest alignment and coalitions in multiparty negotiation. *Acad. Management J.* **41** 42–54.

Powell, W. W., K. W. Koput, L. Smith-Doerr. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Admin. Sci. Quart.* **41** 116.

Ragin, C. C. 2000. *Fuzzy-set Social Science.* The Univ. of Chicago Press, Chicago.

Ragin, C. C. 2005. *From fuzzy sets to crisp truth tables.* Working Paper, University of Arizona.

Ragin, C. C. 2006. Set relations in social research: Evaluating their consistency and coverage. *Political Analysis* **14** 291.

Ragin, C. C. 2008. *Redesigning Social Inquiry*. *Fuzzy Sets and Beyond.* Univ. of Chicago Press, Chicago.

Reagans, R., E. W. Zuckerman. 2001. Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organ. Sci.* **12** 502–517.

Reagans, R., E. W. Zuckerman, B. McEvily. 2004. How to make the team: Social networks vs. demography as criteria for designing effective teams. *Admin. Sci. Quart.* **49** 101–133.

Rihoux, B. 2006. Qualitative comparative analysis (QCA) and related systematic comparative methods. *Int. Sociol.* **21** 679–706.

Roberts, E. B. 2001. Benchmarking global strategic management of technology. *Res. Tech. Management* **44** 25–36.

Rockeach, M. 1960. *Open and Closed Mind. Investigations into the Nature of Belief Systems and Personality Systems.* Basic Books Inc., New York.

Sawyer, J. E., M. A. Houlette, E. L. Yeagley. 2006. Decision performance and diversity structure: Comparing faultlines in convergent, crosscut, and racially homogeneous groups. *Organ. Behav. Human Decision Processes* **99** 1–15.

Schneider, M. R., C. Schulze-Bentrop, M. Paunescu. 2009. Mapping the institutional capital of high-tech firms: A fuzzy-set analysis of capitalist variety and export performance. *J. Int. Bus. Stud.* **41** 246–266.

Sethi, R., D. C. Smith, C. W. Park. 2002. How to kill a team's creativity. *Harvard Bus. Rev.* **80** 16–17.

Smith, K. G., K. A. Smith, J. D. Olian, H. P. Sims, D. P. O'Bannon, J. A. Scully. 1994. Top management team demography and process: The role of social integration and communication. *Admin. Sci. Quart.* **39** 412–438.

Smith, P. G., E. L. Blanck. 2002. From experience: Leading dispersed teams. *J. Product Innovation Management* **19** 294–304.

Stevenson, W. B., J. L. Pearce, L. W. Porter. 1985. The concept of "coalition" in organization theory and research. *Acad. Management Rev.* **10** 256–268.

Swann, W. B., J. T. Polzer, D. C. Seyle, S. J. Ko. 2004. Finding value in diversity: Verification of personal and social self-views in diverse groups. *Acad. Management Rev.* **29** 9–27.

Tajfel, H. 1982. *Social identity and intergroup relations.* Cambridge Univ. Press, Cambridge.

Tajfel, H., J. C. Turner. 1986. The social identity theory of intergroup behavior. S. Worchel, L. W. Austin, eds. *Psychology of Intergroup Relations*. Nelson-Hall, Chicago, 7–24.

Thatcher, S. M. B., K. A. Jehn, E. L. Zanutto. 2003. Cracks in diversity research: The effects of diversity faultlines on conflict and performance. *Group Decision Negotiation* **12** 217–241.

Tidd, J., J. R. Bessant, K. Pavitt. 2001. *Managing Innovation. Integrating Technological, Market and Organizational Change.* Wiley, Chichester.

Van der Vegt, G. S., J. S. Bunderson. 2005. Learning and performance in multidisciplinary teams: The importance of collective team identification. *Acad. Management J.* **48** 532–547.

Van der Vegt, G. S., J. S. Bunderson, A. Oosterhof. 2006. Expertness diversity and interpersonal helping in teams: Why those who need the most end up getting the least. *Acad. Management J.* **49** 877–893.

Van Knippenberg, D., C. K. W. De Dreu, A. C. Homan. 2004. Work group diversity and group performance: An integrative model and research agenda. *J. Appl. Psych.* **89** 1008–1022.

Van Knippenberg, D., M. C. Schippers. 2007. Work group diversity. *Annual Rev. Psych.* **58** 515–541.

Webber, S. S., L. M. Donahue. 2001. Impact of highly and less job-related diversity on work group cohesion and performance: A meta-analysis. *J. Management* **27** 141–162.

West, M. A. 2002. Sparkling fountains or stagnant ponds: An integrative model of creativity and innovation implementation in work groups. *Appl. Psychol. Int. Rev.* **51** 355–387.

Zander, L., C. L. Butler. 2010. Leadership modes: Success strategies for multicultural teams. *Scandinavian J. Management* **26** 258–267.

Zarnoth, P., J. A. Sniezek. 1997. The social influence of confidence in group decision making. *J. Experiment. Soc. Psych.* **33** 345–366.

Zellmer-Bruhn, M. E., M. M. Maloney, A. D. Bhappu, R. Salvador. 2008. When and how do differences matter? An exploration of perceived similarity in teams. *Organ. Behav. Human Decision Processes* **107** 41–59.