TEAM DIVERSITY AND INFORMATION USE

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ABSTRACT

We examined the effects of educational and nationality diversity on work teams' information use. We theorize that some demographic dimensions, such as nationality, trigger social categorization and limit the value of diversity, while other dimensions, such as education, do not cause social categorization and translate directly into cognitive advantages for a team. As expected, increasing educational diversity had positive effects on range and depth of information use for all except the most diverse teams, but had negative effects on how effectively teams used that information. In contrast, increasing nationality diversity was found to have a u-shaped relationship with range of information use and inverted-u relationships with the depth and integration of information use. While group composition has complex relationships with information use, the benefits of improved information processing as a result of both educational and nationality diversity were stronger than the limitations of social categorization processes for all types of information use.

Organizations are increasingly dependent on diverse teams for developing innovative products, making important decisions, and improving efficiency. For example, recent trends in industry such as “integrated product development” are based on the premise that organizations will be more efficient if they bring together a diverse set of experts to solve complex problems (Cagan & Vogel, 2002). Working in diverse teams, however, can be challenging. Although more perspectives may be beneficial, the very nature of these teams’ diversity makes it difficult for team members to communicate, coordinate their work, and perform.

Do all types of diversity have similar effects on team behavior? A large and growing literature on group diversity suggests that different types of diversity have contrasting effects; while positive effects are driven by diverse teams’ access to more information, negative effects of diversity are mainly driven by social processes, such as low cohesion and social categorization, interfering with the teams’ ability to capitalize on increased information. In this paper we study two types of diversity, education and nationality, arguing that educational diversity allows groups to benefit from the informational diversity stemming from heterogeneity in education; while nationality triggers social categorization processes and hinders the team from benefiting from potential informational advantages based on heterogeneous national backgrounds. We further outline non-linear relationships between diversity and three dimensions of information use, acknowledging that the relationships between team diversity and information use may be more complex than previously thought. While our results support the view of educational diversity enhancing groups’ information use, we also find -- contrary to our expectations -- that national diversity has both positive and negative effects on information use. We end by concluding that the potentially inhibiting effects of social categorization on nationality diversity are overridden by the positive effects during later stages of a group’s information processing.

This study examines the effect of educational and nationality diversity on teams’ information use. Information brought to bear is a key determinant of performance on many tasks because effective decisions regarding complex, multifaceted problems require the consideration of multiple perspectives (Katz, 1982;

Cohen & Levinthal, 1990). Consider strategic decisions made by top management teams whose effects cascade down through the organization. Diversity in those teams allows them to tap into a broader array of relevant information, increasing comprehension of the implications of each potential path taken (Hambrick & Mason, 1984; Hambrick, Cho & Chen, 1996). Similarly, in product development, the ability to understand and access information is a key determinant of innovation (Cohen & Levinthal, 1990; Wheelwright & Clark, 1992). Even in seemingly narrow problem domains (e.g., the design of a new circuit board) multiple perspectives (e.g. materials, electrical engineering) can enhance innovation by helping team members reframe a problem. To better understand how diversity influences teams, we need to understand the different types of diversity and how they relate to information use.

In their review of the diversity literature, Williams and O'Reilly (1998) conclude that different types of diversity have different effects, some resulting primarily from changes in information processing and others from social categorization. Our primary goal is to understand how different types of diversity affect a team's use of information. We therefore consider two types of diversity relevant to the performance of complex cognitive tasks: diversity of education and of nationality. Diversity of nationality is a highly relevant aspect of team composition since the proportion of non-US team members in the American work force has increased dramatically over the last decades (NSF, 1999). Diversity of education is also relevant because teams working on complex cognitive tasks in organizations are typically comprised of people with different educational backgrounds (cf. Bantel & Jackson, 1989) which represent distinct thought worlds (Dougherty, 1992). While we expect the effects of educational diversity to be better explained by information processing theories, reflecting the information, knowledge, and skills that people bring to the team (Williams & O' Reilly, 1998); the salient nature of diversity of nationality is better explained by social categorization (Earley & Mosakowski, 2000), a theory which argues that a shared group identity will derive from perceived similarity. In the next section we define educational and nationality diversity. We then hypothesize how diversity is related to three aspects of information use: range, depth, and integration.

Educational and Nationality Diversity in Teams

Educational diversity relates to different sets of task relevant skills, knowledge, and abilities team members possess as a function of their educational background. Education is one of several sources of knowledge that contribute to one's expertise. Expertise provides team members a framework for considering what information is important to the task, which in turn influences what information is attended to and incorporated into the decision (Bunderson & Sutcliffe, 2002; Cohen & Levinthal, 1990). In this research, we focus on diversity in MBA student team members' *dominant* educational background (i.e., their undergraduate majors). Dominant educational diversity is similar to what Bunderson & Sutcliffe (2002) labeled "dominant functional diversity." The two are comparable in that both reflect team members' dominant skills, knowledge, and abilities. The two differ in that dominant *functional* diversity, by focusing on existing functional groups within an organization, provides stronger social categorization cues than dominant *educational* diversity. Functional areas are distinct units (with associated concerns, goals, etc.) to which a member belongs – category labels are clear, people are easily matched with their function, and assumptions about goals and values are easily transferred from the group (social category) to the group member. In contrast, one's educational background is not as easily observed, and thus does not automatically make a person a member of an identifiable, existing group within the organization. A team member's dominant educational background is not as salient to other team members and is not organizationally dictated and thus does not provide the same distinguishing cues. Educational diversity therefore is a purer indicator of informational diversity as discussed by Williams and O'Reilly (1998).

Nationality diversity, in contrast, provides more information about social categories. Defined as the distribution and number of team members' national backgrounds, nationality diversity reflects the trend toward globalization. For example, U.S.-based organizational teams today are more likely to include Asian, South American, or European members than only a decade ago (NSF, 1999). In fact, globalization of the market has been identified as one of the two most significant changes in the work environment in the last decade (Earley

& Gibson, 2002). National origin and culture influence members' values and normative expectations about work behavior (Erez & Earley, 1993). International teams, for example, experience differences in communication styles and patterns (e.g. Gibson, 1996), different norms about information sharing (e.g. Goodman, Ravlin, & Schminke, 1990), and different beliefs about how group work should proceed (e.g. Gibson & Zellmer-Bruhn, 2001).

Research shows that team diversity's effect on *team performance* is not uniform. For example, expertise diversity has been shown to positively influence the team's innovativeness, while other forms of diversity (e.g., age, tenure, and ethnicity) have been shown to interfere with this aspect of team performance (Williams & O'Reilly, 1998). The mechanisms leading to these outcomes, however, have been little explored. In this study, we focus on the mechanism of information use in relation to education and nationality diversity. We expect educational and nationality diversity to affect information use differentially because of their asymmetrical effects on information processing (favoring educational diversity) and social categorization (favoring nationality diversity).

Team Information Use Varies by Diversity

Some theories of group decision-making focus on teams' need to use information fully and effectively to reach high quality decisions and to persuade others of the appropriateness of the decision (Edwards, 1954), whereas others consider how teams attend to, encode, store, retrieve, and process information (Gibson, 2001; Hinsz, Tindale, & Vollrath, 1997; Wegner, 1987). These research paradigms both treat teams as information processors and information use as an important part of team performance.

We argue that team members' perspectives serve as a filter or conduit for potentially unique information that can be applied to the task (Dougherty, 1992; Kilduff, Angelmar & Mehra, 2000), especially during the encoding, retrieval, and processing phases of information processing (Hinsz et al., 1997) or what is referred to as the accumulation, interaction, examination, and accommodation phases of collective cognition (Gibson, 2001). We propose that education and nationality diversity are associated with information use during each step in the collective cognition process. When making complex decisions, teams must first search for relevant information. This occurs in the initial phase of the development of collective cognition – the accumulation phase – when team members perceive, filter, and store information (Gibson, 2001). The variety of team member perspectives directly influences the amount of information available to the team – teams with diverse perspectives have access to a broader *range* of information sources since differences between team members are a direct function of the differences in knowledge among team members (e.g. Dougherty, 1992). A diverse product design team composed of team members trained as mechanical engineers, software engineers, and marketing specialists, for example, should have access to information about how to build the hardware and software components as well as how to evaluate the market for their new product. A team composed only of mechanical engineers, however, is likely to be limited in the information they have beyond hardware and, perhaps, manufacturing considerations.

Once collected, information must be considered in more *depth*. This requires additional exploration of the information acquired, which occurs in the second phase of collective cognition – the interaction phase – where team members retrieve, exchange, and structure information, and also during the examination phase when team members discuss impressions and interpretations of the information at hand (Gibson, 2001). Finally, teams must decide what information is most relevant and should be used. Here team members must decide how to *organize*, integrate, and act on the information – activities which occur in the fourth phase of collective cognition, the accommodation phase. In developing range and depth, and deciding how to integrate and organize that information, team members' perspectives will serve as information filters. Thus, more diverse perspectives translate into access to more potentially relevant pieces of information, a broader set of filters used to determine information relevance, and perhaps a more in-depth knowledge of the implications of that information for the decision taken.

The preceding discussion suggests that teams that differ in their education and nationality diversity will also exhibit differences in range, depth, and integration of information use (what Montoya-Weiss, Massey,

& Song, 2001 refer to as range, depth, and organization of information use). Range is the variety of information included in the team's rationale, "depth" captures the extent to which the arguments or issues raised in the rationale were explored completely, and "integration" is the quality of the structuring of the rationale and the quality of the treatment of interrelationships among the multiple issues. Distinctions between range, depth, and integration highlight different aspects of information use. A team might identify a wide range of relevant issues, but not explore any one in sufficient depth. Or, a team might explore one issue in depth, ignoring other central issues. Finally, adequate attention might be paid to the information at hand, but arguments might not be consistent, resulting in an analysis that is neither logical nor persuasive. A complete understanding of how education and nationality diversity are related to information use requires attention to the range, depth, and integration of information use.

Information Use Depends on Type of Team Diversity

We expect effects of team diversity on information use to be conditioned on the type of diversity (educational versus nationality) and information use (range, depth, or integration). We develop hypotheses describing these relationships drawing from two theoretical perspectives. We theorize that diversity of education acts primarily through differences in information perspectives and that diversity of nationality acts more through a social categorization process (see Williams & O'Reilly, 1998).

Educational diversity and information use. In teams whose task requires processing vast amounts of information (e.g., R & D teams), a team's ability to identify and make use of relevant information can be vital to their success (Katz, 1982; Wheelwright & Clark, 1992). Cohen and Levinthal (1990) have argued that a team's ability to access and use new information, what they label the team's absorptive capacity, should be facilitated by including members with diverse backgrounds. Gaining expertise via formal education means acquiring a body of knowledge and – equally important – the knowledge about where to find additional related information (Wegner, 1987). This knowledge influences the way an individual addresses a given problem and what new information will be noticed and how it will be perceived. According to Bower and Hilgard (1981) we make sense of and acquire new knowledge as a function of the number of categories of prior knowledge (i.e., the *range* of knowledge available), how differentiated these categories are (i.e., the *depth* of knowledge of each of these categories, including how they differ from one another), and linkages between the categories (i.e., the *integration* of knowledge that relate the categories to one another). Thus, the more previous knowledge the individual, team or organization has the easier it is for them to acquire new information and understand its value (Wegner, 1987; Cohen & Levinthal, 1990).

Diversity of team members' educational backgrounds will determine how a team will use information (Cohen & Levinthal, 1990; Bantel & Jackson, 1989; Pelled, Eisenhardt, & Xin, 1999). Range will be influenced because a team consisting of individuals with the same educational background will be more likely to have substantial overlaps in what they know than will a team with members whose educations differ, making for a more focused accumulation stage (Gibson, 2001). For example, three software engineers will engage a narrower range of information than a team composed of a software engineer, an accountant, and a musician when designing an accounting system for a music group. Assuming a relatively non-threatening environment, unique knowledge held by a diverse team should be used by the team (Edmondson, Bohmer, & Pisano, 2001). Thus, we predict that teams with a diverse set of educational backgrounds will use a wider range of information than teams composed of members with similar educations. There may, however, be a saturation point above which an increase in diversity does not add to the ability to use information. When information is shared by at least one other person on the team (as in moderately diverse teams), team members are far more likely to express the information they hold and the information is more likely to be taken into account by the team (Wittenbaum & Stasser, 1996). Teams that are highly diverse in their educational backgrounds may have so little overlap in shared information that they do not trigger others' knowledge, thus limiting the extent to which unique information is conveyed to, understood, and used by the team (e.g. Stasser & Titus, 1985). We therefore argue that more educationally diverse teams will access a broader range of information, but only up to a point.

Hypothesis 1. There will be an inverted-u curvilinear relationship between educational diversity and the range *of information use such that the range will increase with increasing diversity but decrease for teams with the highest levels of educational diversity.*

It might appear that our prediction contradicts Bunderson & Sutcliffe's (2002) findings that teams with members from a wider variety of functional areas ("dominant function diversity") engaged in less information sharing. However, we contend that dominant functional diversity provides social categorization cues because of salient group membership, while educational diversity is not tied to functional assignment and should not trigger social categorization. Thus, whereas functional diversity might suppress information sharing because of social categorization, educational diversity should not.

We argue that educational diversity influences depth of information use up to a point (cf. Cohen & Levinthal, 1990: 135). While information enters the group in the accumulation phase, groups must apply frameworks acquired through education, or develop new ones, to process information in depth during the interaction and examination phases (Gibson, 2001). As educational diversity increases from low to moderate, a more diverse set of pre-existing frameworks is available, and more issues can be explored in greater depth at low cost (Bower & Hilgard, 1981). Alternatively, if team members' frameworks are overlapping (i.e., homogeneous), efforts at processing information will be redundant, resulting in greater depth on some issues, but not enough to compensate for lack of depth on other issues.

Diverse teams have advantages compared to more homogenous ones, both with respect to familiar information -- information that fits at least one team member's framework, and to unfamiliar information -- information that does not fit any team member's framework. As suggested, a diverse team, relative to a less diverse team, has access to a more varied set of frameworks and, thus, will be more likely to already possess relevant frameworks when encountering new information, allowing them to analyze a larger portion of information in depth. At the same time, we expect a diverse team facing a set of information to find a smaller portion of that set to be unfamiliar. A smaller amount of unfamiliar information leaves a group with more time to identify and analyze this information. Thus, a diverse group has *both* less unfamiliar information to analyze *and* more time to do so, providing an advantage in developing depth with respect to unfamiliar information. Therefore, we hypothesize that teams with moderate educational diversity will exhibit greater depth of information use than teams with low educational diversity, since they will have a broader set of frameworks allowing them to classify a larger set of issues as being familiar and hence examine these in greater depth as well as have more time to deeply process information that is deemed unfamiliar.

Educational diversity, like many good things, is good only in moderation. We anticipate that at the highest levels, educational diversity in a team will result in enough disparity of frameworks across experts to demand greater coordination, time, and attentional resources in the accommodation phase. Further, team members who have too little common ground can have problems understanding each other (Krauss & Fussell, 1990) and are not well positioned to explore shared ideas fully. Consequently, we hypothesize:

> *Hypothesis 2. There will be an inverted-u curvilinear relationship between educational diversity and the* ***depth*** *of information use such that the depth will increase with increasing diversity but decrease for teams with the highest levels of educational diversity.*

Finally, we consider the effect of educational diversity on the integration of information. Integration of information is the extent to which logical linkages are made between items of information (see Bower & Hilgard, 1981). When unique information comes from different team members, developing these linkages requires integrating knowledge across team members. Knowledge integration occurs via interaction among team members which allows them to learn from one another and develop a collective knowledge that facilitates communication and action (Sole & Edmondson, 2002). Integrating this knowledge, however, may be difficult in diverse teams because team members do not share the common conceptual ground required to connect these pieces of information and develop the shared understanding (Krauss & Fussell, 1990) required to ensure logical consistency. Greater differences in educational background in combination with the wider information space considered in diverse teams thus makes effective integration of information more difficult to accomplish.

> *Hypothesis 3. A team with more educational diversity will exhibit lower* ***integration*** *of information than*

will a less diverse team.

Nationality diversity and information use. Although teams with nationality diversity may have different worldviews and perceptions that can positively influence information use (Goodman et al., 1990; Choi, Nisbett, & Norenzayan, 1999), we argue that nationality diversity is more likely to result in social categorization, a process that emphasizes group distinctions and can interfere with a team's ability to use information. Social categorization suggests that individuals seek to bolster their in-group and derogate out-groups as a way of enhancing their own self-construals. Although different contexts may trigger different identities (see Lau & Murnighan, 1998), nationality has been acknowledged as a superordinate determinant of identity and is likely to be even more salient than culture, race, gender, and other status-determining traits (Earley & Mozakowski, 2000; Hambrick, Davison, Snell, & Snow, 1998). Being such a salient characteristic, nationality diversity might segment the team and interfere with team members' ability to work together effectively (Tajfel, 1981; Turner, 1987; Harrison, Price, & Bell, 1998).

Social categorization effects are most likely to occur in groups with moderate heterogeneity in which distinct (i.e., strong) subgroups can form (Earley & Mozakowski, 2000; Gibson & Vermeulen, 2003). By definition, groups with moderate nationality diversity have members that share national origin. We expect members with the same national origin to coalesce into subgroups, reinforcing one another and differentiating themselves from other subgroups in the team (Earley & Mozakowski, 2000; also Cramton & Hinds, 2005). We argue that nationality, being a salient social category, will likely cause the formation of strong sub-categories in moderately diverse teams.

Groups that are highly diverse, such that (almost) all team members differ in national origin, and groups that are homogeneous, such that (almost) all team members are of the same national origin, do not have the opportunity to form subgroups based on national origin, and thus are less likely to experience social categorization (Cramton & Hinds, 2005; Earley & Mozakowski, 2000). Instead highly nationally-homogeneous groups will act as a cohort and nationally-heterogeneous groups will attempt to establish a shared understanding of what it means to be a member of a diverse group, developing a unique identity for the team (Earley & Mozakowski, 2000), perhaps derived from their diversity rather than their similarities (Gibson & Vermeulen, 2003). Thus, we would expect highly diverse teams, like homogeneous teams, to be more likely to coalesce into a single group rather than into distinct sub-groups (Earley & Mozakowski, 2000; Gibson & Vermeulen, 2003). More specifically, we expect a u-shaped relationship between nationality diversity and information use. While previous research has demonstrated this form of relationship between nationality diversity and team performance in more mature teams (Earley & Mosakowski, 2000) and between team heterogeneity and team learning behaviors when subgroups are strong (Gibson & Vermeulen, 2003), ours is the first study to hypothesize this curvilinear effect on information use.

We argue that social categorization and resulting subgroup formation that occurs in moderately diverse teams will interfere with the team's ability to use information. Although teams with nationality diversity are likely to bring different perspectives and experiences, these differences must be relevant to the task at hand to influence the range of information use. Thus, we do not expect an informational advantage for more nationally-diverse teams. Instead, the splintering of the team into identifiable subgroups (in-groups vs. out-groups) should interfere with their ability to access and use the information they have available to them. We expect nationality diversity to interfere with the team's ability to develop range and depth in any given domain and to organize information in a coherent way. Range of information use requires team members to share information with the team and for the team to accept the information as worthy of consideration. Members of teams with identifiable subgroups are less likely to accept ideas that come from subgroups other than their own, thus reducing the range of information used. Depth of information use requires more complex consideration of information, which will be difficult to achieve for teams whose members are focused on sub-group membership because it will be difficult to generate consensus for exploring any one perspective in depth. Similarly, integration of information requires making connections across domains which in turn requires collaboration between people, something that is difficult to do in splintered teams. These arguments are consistent with Earley and Mozakowski's (2000) finding that teams with less nationality diversity communicated more effectively, in part because they were more willing to listen to one another. Earley and Mozakowski, however, also noted that teams with the highest levels of nationality diversity were effective at sharing their different perspectives. We therefore predict that teams with more nationality diversity will exhibit less range, depth, and integration of information, but only up to a point. At high levels of nationality diversity, we anticipate that teams will achieve increased range, depth, and coherence.

> *Hypothesis 4. There will be a u-shaped curvilinear relationship between diversity of nationality and **range** of information use such that range will decrease with increasing diversity, but increase for teams with the highest levels of diversity of nationality.*

> *Hypothesis 5. There will be a u-shaped curvilinear relationship between diversity of nationality and **depth** of information use such that depth will decrease with increasing diversity, but increase for teams with the highest levels of diversity of nationality.*

> *Hypothesis 6. There will be a u-shaped curvilinear relationship between diversity of nationality and **integration** of information use such that integration will decrease with increasing diversity, but increase for teams with the highest levels of diversity of nationality.*

METHOD

Setting and Sample

As part of a 7-week introductory MBA organizational behavior course, 135 students were randomly assigned to teams and completed four case analyses involving organizational problems. Each team selected from a set of six unique cases and we randomly selected three of these six cases to analyze (with consent from participants). As a result, we had between one and three observations per team depending on their selection of cases. Given that our data contains repeated measures, to control for multiple observations per team, we had to exclude single-observation teams (n = 6). We also dropped 2 teams in which no members completed a final questionnaire. Our final data set consisted of 45 case analyses completed by 100 participants on 19 teams (including one four-person team, 14 five-person teams and four six-person teams).

We saw several advantages in using this sample. First, although in an educational rather than organizational context, the teams under study were performing a task in a naturalistic setting, allowing us to obtain unobtrusive observational data. Second, the context had the desirable qualities of (1) highly motivated individuals whose grades depended upon team performance, (2) teams that varied on educational and nationality diversity while being relatively invariant on other diversity dimensions (among the 100 students, 17 were women and two were African-Americans, there was also little variance in age (M=27, SD=3.5 years) and work experience (M=3.8, SD=2.6 years)), (3) team membership persisted over two months, and (4) identical tasks for which all teams received the same background information. These conditions provided a controlled, naturalistic situation to evaluate information use.

Task

The team task was to analyze and generate solutions to organizational problems presented in Harvard Business School cases. Cases are a popular method used to train students in problem identification and analysis, an important skill for managers. The task has external validity. Similar tasks are performed in organizations when groups are asked to develop policies, juries are asked to reach a verdict, consultants – both technical and management—are asked to evaluate competing bids or suggestions for business. All these tasks involve receiving a large and conflicting body of information that needs to be processed with respect to multiple perspectives (i.e. range), in sufficient detail (i.e. depth) and then these perspectives need to be well integrated into a final report or verdict (i.e. organized).

Measures

Educational diversity. Educational diversity was measured in terms of participants' undergraduate major. We considered undergraduate major a good proxy for educational background because students in our sample were not far removed from their undergraduate studies, with less than 4 years of work experience on average. Students reported 32 unique undergraduate majors, the most common majors being economics, electrical, mechanical, and industrial engineering, computer science, and business administration. We coded down to the level of engineering sub-specialties to be able to differentiate between ten undergraduate degrees. For example, we expected an industrial engineer to be more sensitive to issues surrounding manufacturing interfaces (such as conflict between sales and manufacturing, as portrayed in one case) and that mechanical engineers would react more to product design issues (one case discusses using an old product for new applications). To calculate diversity we used Blau's (1977) index, $(1-\sum p_i^2)$, where p_i is the fraction of team members with major *i*. Blau's index treats the data as categorical, therefore we need not make any assumptions about how different majors are from one another. All teams in our sample were on the high end of Blau's index for educational diversity (M = .76, ranging from 0.56 to 0.83, see Table 1).

Insert Table 1 about here

Nationality diversity. Nationality diversity was based on team members' dominant national affiliations. We had information on country of citizenship for all students and on nation of birth and native language for the large majority of students (n = 90, 90%). These three pieces of information (citizenship, nation of birth, and native language), when available, were always consistent, and thus provided a reliable measure of nationality. We used country of citizenship for the remaining 10 students (eight Japanese and two US citizens). The 100 participants came from 23 different countries and 45 were non-U.S. Of the 45 non-US students, 29% came from Europe, 27% from Japan, 20% from Asia excluding Japan, 9% from Latin America, 7% from the Caribbean and 5% from Canada. The average number of nationalities represented in a team was three, ranging between one and five (Blau's index: M = .55, ranging from 0.0 for a six-member team in which all members came from the U.S. to 0.8 for a five-person team in which all members came from different countries). All teams had at least one US citizen and in all teams but one, US members equaled or outnumbered any other nationality.

Information use: range, depth, and integration. For our measures of range, depth and integration, we coded the case write-ups produced by the teams in our study. Our measures of information use were designed to capture the *application* of information rather than the *process* of using information. That is, we focused on how people "used" (or applied) the information in their analysis of the problem. We see this as an outcome of the information use process, a process which influences a final product (e.g., overall quality of analysis or decision taken). We believe our method of measuring information use is intermediate between directly capturing process (a more dynamic concept) and final product (an overall judgment of outcome).

For the range and depth measures, each case was first divided into segments (unitized) and then each unit was classified along two dimensions in a code scheme by four Organizational Behavior Ph.D. students who were blind to the hypotheses. Units were defined as *a meaningful action* for an organization or person described in the case, and thus had to contain at least one verb and could include up to one sentence. The case write-ups included between 60 and 229 units, 10% of which were checked for unitizing reliability, which was high (i.e., very low disagreement: Guetzkow's (1950) U = .03).

Unitized segments were coded along two dimensions: type of statement and topic. The first dimension, the type of statement, identified whether the statement was (1) descriptive/analytic, (2) a suggestion, or (3) reflected the outcome of a suggestion. Only descriptive/analytical units were used when calculating information use because we were interested in information analysis rather than how information was translated into action by the teams. In these units, information from the case description was repeated, problems identified, and causal linkages between problems suggested. The inter-rater reliability for identifying the descriptive/analytic units was high: Cohen's kappa (1960) varied between .77 and .86 across the cases, indicating excellent agreement (Fleiss, 1981). The second dimension was case-specific and captured the different content categories. For example, one case, concerned with goal alignment between organizational units, included categories such as "corporate – region goal alignment" and "incentive structure for sales personnel", while another case focused on conflict in a management team included content categories such as "manufacturing – marketing tension" and "leadership style." Agreement between coders in identifying which topics were present versus absent in the analysis was good (Cohen's kappa = .64; Fleiss, 1981).

Our *range* measure counted the number of content categories in a group's analysis (derived from the coding described above) (Montoya-Weiss et al., 2001; Watson, Kuman, & Michaelsen, 1993; Suedfeld, Tetlock & Streufert's, 1992, *differentiation* measure). If a topic was mentioned at least once, it was counted as present (1), otherwise absent (0). Code schemes for the different cases identified 40, 42 and 56 available topics with the maximum identified by any team being 33, 37 and 38 topics respectively. We standardized for the number of topics available to control for differences across cases, resulting in a measure that reflects a team's range of information use relative to that of other teams (M = 0.03, ranging from -1.80 to +1.79).

The *depth* measure captured the average amount of information presented within each covered topic (Montoya-Weiss et al., 2001), operationalized by calculating the average number of descriptive/analytical units per topic identified in the case write-up. The depth measure allowed for repetition of ideas because the same information might be used to make different points. However, we did control for amount of text (i.e., wordiness) recognizing that the depth measure could be artificially inflated by verbosity. To make comparisons across cases possible, we also standardized the depth measure for each case (M = 0.09, ranging from -1.76 to +2.97).

The *integration* measure captured the consideration of relationships among diverse issues (see Watson et al., 1993; and Suedfeld et al., 1992, integration measure). Three Ph.D. students, trained on a separate set of case write-ups and unaware of the hypotheses and authors of the write-ups, were each provided with case-specific lists of possible problems/issues and were trained to rate the quality of the integration of the analysis for each general issue – that is, whether arguments were well founded and provided causal linkages between topics raised within an issue (Montoya-Weiss et al.'s, 2001, intrarelationships within relevant issues). Integration was measured on a 5-point scale. This measure was different than the others; while depth and range were a *count* of relevant topics, integration assessed how well the arguments across topics within an issue fit together. Inter-rater reliability was high (r = .88). Ratings were averaged across issues identified for each write-up to produce an overall measure of integration. As with the other information use measures, we standardized the integration measure for each case (M = -.01, range -2.87 to +1.50).

Control Variables

We included seven control variables. Four variables addressed other compositional characteristics of the teams: number of bi-cultural team members, average proficiency with American English, gender composition, and team size. Two control variables addressed team processes: team conflict and delegation strategy. The final control, text length, related to the output of the team. See Table 1 for means and standard deviations.

Bi-cultural members. Many of the non-US students received their undergraduate degree in the U.S. We refer to this group as "bi-culturals" because they have significant life experiences in multiple cultures.[1] Non-U.S. students with undergraduate experience in the U.S. should be more accustomed to and more likely to adopt U.S. norms and customs as compared to non-U.S. students without such experience. As a result, other team members should find it more difficult to cleanly assign them to social categories related to nationality since, in some ways, they belong to two: one by virtue of birth and a second by virtue of their U.S. undergraduate educational experiences. Because these "bi-culturals" do not cleanly reflect a non-U.S. nationality, their presence could dilute the effects of nationality diversity. In our sample, bi-culturals represented 23% of the non-US team members. Teams had between zero and two bi-cultural team members, with eight having none, nine having one, and two having two bi-cultural team members.

English proficiency. We controlled for American English language proficiency using teams' average TOEFL scores. This control helps rule out the explanation that findings related to nationality diversity could be due to highly diverse teams having lower English proficiency. TOEFL (Test of English as a Foreign Language) measures the ability of nonnative English speakers to use and understand North American English as it is spoken, written and heard in college and university settings. The test is taken by nonnative English speakers applying to US colleges and universities. Because we needed a team level measure of English proficiency

[1] We recognize that these people may not be bi-cultural in their self-identity, however, we chose to use this label to represent their knowledge of both cultures rather than to connote a divided identity (see LaFromboise, Coleman & Gerton, 1993).

and TOEFL scores for the native English speakers in our sample did not exist (they were not required to take the test), we imputed normally distributed data based on a six percent higher average score and a standard deviation 13 percent lower for the native english speakers compared to the non-native speakers (TOEFL score = 651.47, st.dev. = 27.00). We chose the mean and standard deviation values based on observed differences in GMAT scores between native and non-native speakers, based on TOEFL's claim that the results on the TOEFL test should be similar to those on the language portion of the GRE and GMAT tests (TOEFL, 2004)[2]. We then calculated the average TOEFL score for each group.

Gender. We used the number of female team members as a control for gender composition. Seven of 19 teams were all male, but there were no all female teams (max = 3 females/team).

Team size. We controlled for team size to rule out the possible alternative explanation that larger teams have the potential to be more diverse and therefore might be driving any diversity effects.

Team conflict. Team conflict was assessed to rule out the possibility that diversity effects (positive or negative) might be due to increased conflict in the team (e.g., Pelled et al., 1999). Team conflict (5-items, alpha = .77, 1 = low conflict to 5 = high conflict) was measured in a questionnaire at the end of the semester in which we asked students to rate the level of conflict during the entire 7-week course. The questionnaire was completed by 94 students, of which 30 failed to identify their team, leaving us 64 (64%) usable questionnaires (M = 3 questionnaires/team). For teams with at least two members answering the questionnaire, a group mean was constructed (within-group agreement: $r_{wg(j)}$ = .66; James, Demaree, & Wolf, 1984). A sensitivity analysis, separating the single-respondent groups (n = 3) from the multiple-respondent groups revealed no differences, allowing us to use the individual value for those three teams.

Delegation strategy. To capture the possibility that some teams might have circumvented their

[2] We performed sensitivity analyses, analyzing whether estimations differed when we imputed values using (1) the average score and standard deviation of native English speakers as presented by TOEFL (TOEFL, 2004); and (2) the average score and standard devaitation of non-native speakers in the population. Results changed marginally for the TOEFL variable and did not alter the coefficients for theoretical variables. Finally, we ran all analyses using the standard deviation, rather than the average, of groups' toefl scores. Again, this made no difference to the results.

diversity by assigning the case to only one team member, we controlled for delegation strategy. In the end-of-semester questionnaire team members were asked to report the delegation strategy used for each case on which they had worked. Groups for which all respondents indicated the case write-up had been produced by only one individual were coded “1” and all other groups (who used other delegation methods that involved more than one group member) were coded “0”.

Text length. To control for repetitive statements and general wordiness that might inflate the range and depth measures, we counted the total number of units in each case write-up.

Other controls. We tested but did not include the following control variables because they had no reliable effects: average age, average GMAT score, average years of work experience, previous degrees in Psychology or OB, and dummy variables for each case.

RESULTS

Correlations between variables (see Table 1) reveal that depth of information use was positively associated with range and integration, suggesting that teams that explored each topic more thoroughly also covered more topics and identified linkages across issues. Length of case (i.e., total units) was associated with range and depth, but not integration. This confirms that our integration measure had little to do with the amount of material covered in the case write-up.

To test our hypotheses, we used GLS regression analyses for panel data with an autoregressive correction (AR1) (Greene, 2000). This formulation corrects for multiple observations per group which by definition are NOT independent, allowing us to use the full set of 45 cases. More specifically, the panel data formulation handles data with repeated observations (i.e., multiple cases per team) by assigning a group fixed effect that controls for aspects of teams not captured by our measures (for instance groups choosing different task strategies or different leadership models). The GLS formulation also allows for autocorrelation within panels and heteroscedasticity across panels. The autocorrelation correction helps control for dependencies in residuals across the different cases and the heteroscedasticity correction compensates for the possibility that our models might explain more variance for one case than for another. This allows us to account for the fact that the cases differ in terms of complexity, length, issue salience, etc.

Range of Information

We predicted that *range of information use* would be positively influenced by educational diversity, but only to a point (H1), and negatively influenced by nationality diversity, but only up to a point (H4). Regression results showed a significant positive linear ($z = 76.90$, $p < .01$) and negative curvilinear ($z = -52.50$, $p < .01$) relationship for educational diversity (see Table 2, Model 2), suggesting a positive, but inverted-u slope supporting H1. Diversity of nationality had a significant negative linear ($z = -6.62$, $p < .01$) and a significant positive curvilinear ($z = 6.34$, $p < .01$) relationship with information range (see Table 2, Model 2). This u-shaped relationship supported H4.

Comparing the effect of educational diversity with that of nationality diversity, we found that the curvilinear effect of educational diversity was significantly greater than the curvilinear effect of nationality diversity (chi-square (1) = 21.30 $p<.01$). See Figures 1a and 1b for plots of the predicted values of range of information use as a function of diversity.

Insert Table 2 and Figure 1 about here

Depth of Information

We hypothesized an inverted-u curvilinear effect of educational diversity on depth of information use (H2) and a u-shaped curvilinear effect of nationality diversity on depth of information use (H5). Hypothesis 2 was supported in that the curvilinear relationship between educational diversity and depth of information use was significant in the predicted direction ($z = 87.03$ for educational diversity and $z = -63.29$ for educational diversity-squared, both $p < .01$, Model 4). Hypothesis 5 was not supported in that the relationship between nationality diversity and depth was an inverted-u ($z = 8.41$ for nationality diversity and $z = -8.80$ for nationality diversity squared, both $p < .05$, Model 4). Again the effect of educational diversity was stronger than the effect of nationality diversity (chi-square (1) = 10.03, $p < .01$). See Figures 1a and 1b for plots of the predicted values of depth of information use as a function of diversity.

Integration of Information

We hypothesized a negative linear effect of educational diversity (H3) and a u-shaped curvilinear effect of nationality diversity (H6) on integration of information. Model 6 (Table 2) shows support for Hypothesis 3 (educational diversity: $z = -2.14$, $p < .05$) (see Figure 1a).[3] Nationality diversity, however, was found to have a positive ($z = 11.09$, $p < .01$) and inverted-u curvilinear effect ($z = -11.23$, $p < .01$) on integration (see Table 2, Model 6; Figure 1b). Thus, H6 was not supported. As before, the effect of educational diversity was stronger than that of nationality diversity (chi-square (1) = 9.68, $p < .01$).

Control Variables

As a set, the control variables were most influential for the depth of information use, as compared to the range and integration. Characteristics of the team itself (bi-culturals, English proficiency, gender and size), their process (amount of conflict), and their verbosity (text length) all influenced depth to varying degrees (see Table 2, Model 4). Each of the control variables had effects on different dependent variables, but the effects were not consistent within control variable type (team characteristics, process, or verbosity).

DISCUSSION

We predicted and found that different types of diversity (educational and nationality) in small teams differentially influence information use. We also confirmed that there are several dimensions of information use in small teams – range, depth, and integration – each with a different relationship to diversity. This work suggests that the relationship between diversity and information use may be more nuanced than previously believed and that treating information use as a single construct may obscure important differences.

Diversity of education had stronger effects on range, depth, and integration of information use than did nationality. This is not surprising, and perhaps comforting, in that diversity dimensions such as education

[3] Although not hypothesized, we tested for, but did not find, a curvilinear relationship between educational diversity and organization.

mirror a true difference in perceptions and knowledge and have direct relevance for the task at hand, while nationality has less direct relevance to the task. What makes these results especially interesting is that the two types of diversity had different effects on information use. As predicted, educational diversity had inverted-u curvilinear effects on range and depth of information use and a negative effect on integration and nationality diversity had a u-shaped curvilinear relationship with range. But, contrary to predictions, nationality diversity had an inverted-u relationship with depth and to a lesser degree an inverted-u relationship with integration suggesting benefits to diversity of nationality we did not anticipate (see Figures 1a and b for illustrations of the relationships).

Our results point to ways that educational diversity can both help and hinder teams' ability to use information. More diverse teams used a broader range of information, but only up to a point. At high levels of educational diversity, further increases resulted in a decrease in range back to the mean of the sample. Teams with more educational diversity also engaged in more depth of information use, however at the highest levels of diversity teams returned to more shallow analyses, equivalent to teams with the lowest diversity in our sample. These curvilinear relationships confirm Cohen and Levinthal's (1990) argument that teams reach a saturation point above which they no longer continue to gain benefits from diversity, albeit their argument was one of diminishing returns rather than decline at high levels.

Teams that were more diverse in education were less able to organize the information they identified, and this relationship was linear, as predicted. Educationally diverse teams were less able to make connections across topics within issues. Drawing connections requires knowledge about each relevant content area. In that educationally diverse teams have distributed knowledge of the content, they have more difficulty making linkages because they have to bridge across team members. In sum, educational diversity can both help and hinder a team's ability to use information. While some diversity in educational background will increase the amount of information available to the team, too much makes it difficult to access, explore and link this information. In situations where the integration of information is of great importance, special attention and time needs to be allocated to the integration aspect of group cognition (Gibson, 2001).

As teams' nationality diversity increased from low to moderate levels, they used a narrower range of information but considered that information in more depth and with higher integration. However, as nationality diversity increased from moderate to high levels, teams' range of information use increased, while depth and integration dropped off. These findings suggest that the influence of nationality diversity, and social categorization by extension, is different than we hypothesized.

Nationality diversity had unanticipated benefits on information use, and while social categorization resulting from nationality diversity might have interfered with teams' ability to access a broad range of information, it did not interfere with their ability to explore that information in greater depth nor use that information in a coherent way. These findings contradict those of Earley and Mozakowski (2000), where moderate levels of nationality diversity interfered with information use. In fact, moderate nationality diversity stimulated more depth and higher integration. Benefits from diversity of worldviews (Alderfer & Smith, 1982; Cox, 1993) and cognitive orientations (Choi et al., 1999) seemed to dominate negative effects of social categorization in these groups

To understand the effects of nationality diversity, we consider range, depth, and integration as sequential processes. As we argued earlier, range is accomplished at the accumulation phase, depth at the interaction and examination stages, and integration at the accommodation phase. For an issue to be developed (depth), it must first be identified (range). For an issue to be well-analyzed (integration), some in-depth understanding of the idea must first be generated. Based on our results, we conjecture that social categorization processes may mainly affect the accumulation phase – disrupting the introduction of new ideas into the group. However, once an idea has made it past the social category filter and entered the group, team members' different worldviews and cognitive orientations may enable more depth of processing and better linkages across topics. This is not to say that social categorizations become irrelevant at later stages, rather that different ways of thinking about the information accumulated by the group may outweigh the polarizing effects of social categorization. A side benefit of a narrowed range of information identified during the accumulation phase in these groups is that it increases the team's ability to process that information because more resources are available. As argued by Gibson (2001), there is a tradeoff between variety of information and a teams' ability to effectively integrate the information available to them. With less variety of information, teams are better positioned to analyze and structure new information.

Another possible explanation for these results lies in our earlier point that the salience of the demographic factors upon which diversity is based determines its effects. Social categorization, unlike informational effects, must be perceived by the team members in order to have the hypothesized effects. It is possible that differences in national origin were at first noticeable, but faded into the background as the team members got to know one another and identified points of similarity (Zellmer-Bruhn, Maloney, Bhappu, & Salvador, 2004). If this happened, one would expect range to suffer, but processing at later stages (interaction, examination, and accommodation) to benefit from nationality diversity as social categorization along national boundaries diminishes. This is consistent with our findings. Future research that measures the salience of social categories over time will be needed to evaluate this explanation.

These results suggest that previous studies relating diversity to team performance should be reconsidered in terms of their information-usage requirements. In generalizing to organizational teams, we consider the role of expertise diversity (in the absence of associated functional categories), as opposed to the more narrow operationalization used in this study – educational diversity. We believe this is reasonable because the dominant sources of expertise diversity vary beyond education at later career stages. Teams whose performance is highly dependent on accessing a broad range of information (market research teams, juries, R&D teams) can benefit from expertise and nationality diversity, but in specific ways. Diversity provides teams the opportunity to tap into multiple, unique perspectives on the task (Cohen & Levinthal, 1990; Tushman & Scanlan, 1981) that can best be capitalized on by moderate expertise-diverse teams (to avoid information overload) and low (and perhaps very high) nationally-diverse teams (to avoid pitfalls of social categorization). Teams that require greater depth of information processing (e.g., product development teams) can benefit from moderate levels of both expertise and nationality diversity, and they may be especially vulnerable to the risks of high diversity. Too much diversity can make it difficult for team members to flesh out a given perspective in any depth, perhaps due to competing attention across issues when team members are diverse. Finally, teams that require complex linkages across unique information (e.g., top management teams) might suffer when expertise diversity is high but benefit when nationality diversity is moderate to high. While information held by different experts in the group might interfere with the team's ability to integrate the information, national differences add richness of insight that cross-cuts these divisions.

Overall, this study suggests that diversity has a complex relationship with information use. This is undoubtedly due to team processes. Our results suggest that the effects of diversity on information use occurred regardless of the level of conflict or the presence of bi-culturals in the team. As we suspected, bi-cultural team members, or members who have experience in two countries or cultures, help the team capitalize on its diversity by increasing their range and depth of information use. Conflict, in contrast, interfered with range and somewhat with depth of information use.

There are several limitations to the study. First, our participants were students. Although this provides many advantages in terms of control, we recognize that student teams operate in a different context than organizational teams where the organization has a stake in the team's work. Having said that, academic institutions have much at stake regarding how to integrate international students into student work teams: Among *Business Week's* top 30 U.S. B-schools, non-U.S. students account for 34.3% of the average MBA class (Business Week, 2003). Another key difference between student teams and teams within organizations, is the time horizon. Absorptive capacity is claimed to have cumulative properties (Cohen & Levinthal, 1990) which makes it likely that teams that use a wide range of information will increase their performance more than those with a more limited range, at least until a saturation level is reached. Thus, diversity might become more beneficial over time as teams develop a better understanding of how to tap into the expertise that resides in the team. Longitudinal field research is necessary to understand the effects of time on the relationship between diversity and information use.

Another limitation of our study was a small sample size and restricted range in terms of educational diversity (our sample did not include relatively homogeneous teams). A larger sample would have provided a more powerful test of our hypotheses and lessened the possibility of erroneous results. Inclusion of low educational-diversity teams would have provided a more complete picture of the form of its relationship with information use. We recognize the challenges of conducting field research with large numbers of teams, but believe this is an important next step.

Although our results need to be replicated and more questions answered before recommendations for practice are clear, we submit one suggestion. In that expertise and nationality diversity frequently co-occur in organizational teams, it is important to consider their combined effects. Recent research suggests that cross-cutting types of diversity may help to maximize its benefits. Cross-cutting expertise and nationality may weaken social categorization while maximizing information processing. A team with five mechanical engineers and three marketing specialists, for example, may use information less effectively if the engineers are from India and the marketing specialists from the U.S. as opposed to being split across those categories (Lau & Murnighan, 1998). We therefore suggest that, to the extent that managers have control over the composition of their teams, they seek to compose teams such that attributes invoking social categorization (e.g. nationality) are cross-cut with attributes that promote information processing (e.g. expertise).

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TABLE 1

Descriptive Statistics and Correlations

	Mean (st.dev.)	1	2	3	4	5	6	7	8	9	10	11	12
1. Range	.03 (.90)	1											
2. Depth	.09 (.99)	.30*	1										
3. Organization	-.01 (.95)	.02	.44**	1									
4. Educational Diversity	.76 (.07)	-.01	-.25+	-.18	1								
5. Nationality Diversity	.55 (.17)	-.07	-.04	.10	-.20	1							
6. Bi-culturals	.51 (.69)	-.02	-.04	-.00	.11	.63**	1						
7. English Proficiency (TOEFL)	626.66 (9.89)	-.20	-.21	-.36*	.33*	-.16	.18	1					
8. Gender (# of females)	.88 (.88)	-.01	.24	.00	-.12	.14	.02	.10	1				
9. Group Size	5.11 (.49)	.10	.09	-.14	-.01	.18	.30*	-.09	.35*	1			
10. Conflict	2.91 (.81)	-.21	-.07	-.04	.11	.49**	.60**	.34*	.41**	.38*	1		
11. Delegation Strategy	0.18 (.39)	.06	-.00	-.39	.06	-.20	-.09	.36	.19	.25+	-.02	1	
12. Total Units	136.51 (37.82)	.68**	.59**	.16	-.17	-.02	-.02	.34*	-.02	.11	-.13	.04	1

+p<.10, * p<.05, ** p<.01

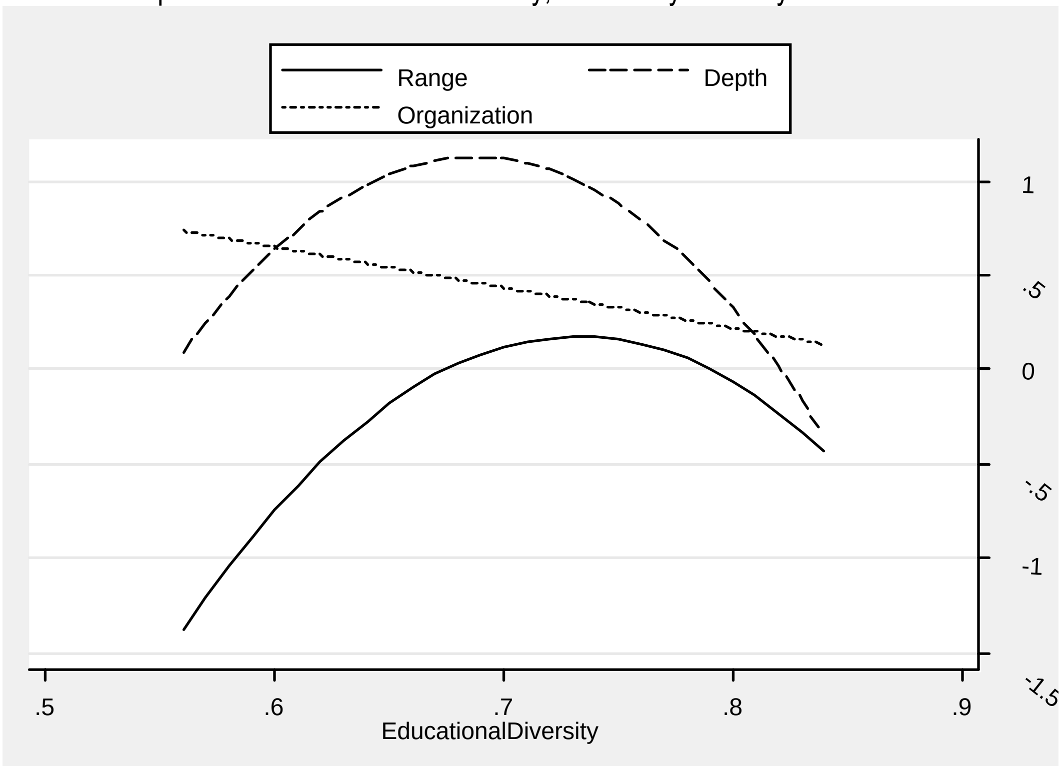
TABLE 2 : Results of Panel Data GLS Regression Analyses with Autoregressive Correction

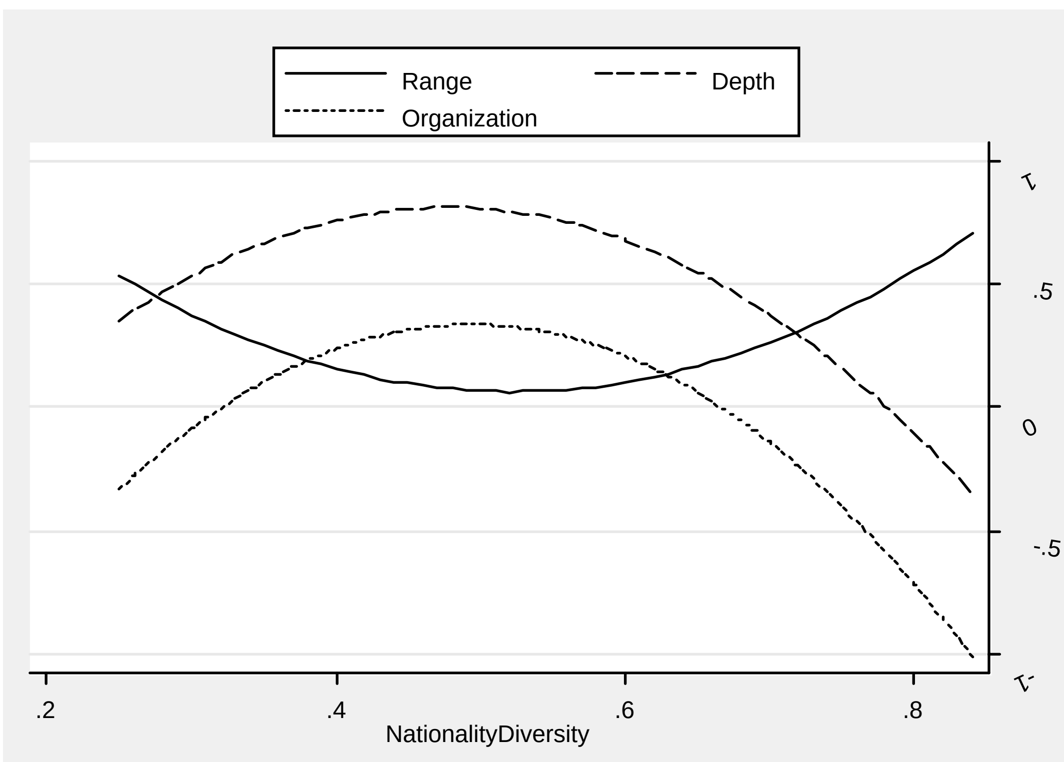
	Range of Information Use		Depth of Information Use		Organization of Information Use	
	1 Control model	2 Full model	3 Control model	4 Full model	5 Control model	6 Full model
Constant	2.66 (5.84)	-22.06 (8.43)***	-.54 (5.48)	-46.23 (12.82)**	16.13 (6.92)*	12.88 (7.48)+
Educational diversity		76.90 (18.41)**		87.03 (23.66)**		-2.14 (1.06)*
Educational Diversity - squared		-52.50 (13.11)**		-63.29 (16.93)**		
Nationality Diversity		-6.62 (1.91)**		8.41 (4.29)*		11.09 (3.68)**
Nation. Diversity - squared		6.34 (1.88)**		-8.80 (4.32)*		-11.23 (3.72)**
Control Variables						
Bi-culturals	.05 (.16)	.27 (.13)*	.03 (.11)	.37 (.20)+	-.00 (.16)	.16 (.18)
English Proficiency	-.08 (.08)	-.10 (.07)	-.05 (.08)	.18 (.10)+	-.25 (.10)*	-.21 (.11)+
Gender	.03 (.08)	-.08 (.06)	.32 (.10)**	.28 (.13)*	.25 (.10)*	.30 (.11)**
Size	.11 (.17)	.24 (.13)+	.31 (.27)	.54 (.25)*	-.24 (.22)	-.40 (.20)*
Conflict	-.24 (.10)*	-.40 (.10)**	-.09 (.12)	-.20 (.10)+	-.03 (.15)	.19 (.17)
Delegation Strategy	.14 (.20)	.02 (.17)	.08 (.19)	-.28 (.18)	-.94 (.27)**	-.74 (.31)*
Total Units	.16 (.02)**	.15 (.01)**	.14 (.02)**	.14 (.02)**	.05 (.02)*	.05 (.03)*
Log likelihood	-23.20	-14.09	-25.96	-22.29	-41.24	-40.14
Wald chi-square	151.61**	932.21**	104.29**	161.32**	54.28**	60.79**
df	*7*	*11*	*7*	*11*	*7*	*10*

+p<.10, *p<.05, **p<.01. The variables “total units” and “English proficiency” are divided by 10 to scale coefficients and standard errors.

FIGURES 1A AND 1B

Relationships between Educational Diversity, Nationality Diversity and Information Use





Bio Statements

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Kristina B. Dahlin is an Assistant Professor in Strategy & Organization at the Joseph L. Rotman School of Management, University of Toronto. Her Ph.D. is in Organizational Behavior and Theory from Carnegie Mellon University. Her research focus is organizational learning, studying how firms' react to a sequence of unforseen events. She has examined firm learning through radical product innovations in the tennis racket industry and accident reductions in the freight railroad industry. Parallell interest areas are the role of independent inventors as well as the measurement and evolution of technology. She has recently published in *Research Policy* on these topics.

Laurie R. Weingart

Laurie R. Weingart is a Professor of Organizational Behavior at the David A. Tepper School of Business, Carnegie Mellon University. She holds a Ph.D. in Organizational Behavior from the J.L. Kellogg School of Management at Northwestern University. Her research focuses on conflict management in work groups and the tactical behavior and cognitive processes of negotiators in both dyads and groups. Dr. Weingart publishes in top-tier management and social psychology journals, has served in leadership roles in both the Conflict Management Division of the Academy of Management and the International Association for Conflict Management, and serves on the editorial boards of *Academy of Management Review*, *International Journal of Conflict Management*, *Journal of Personality and Social Psychology,* and *Organizational Behavior and Human Decision Processes*.

Pamela J. Hinds

Pamela J. Hinds is an Assistant Professor with the Center on Work, Technology, & Organization in the Department of Management Science & Engineering, Stanford University. She conducts research on the effects of technology on groups. Much of her research has focused the dynamics of geographically distributed work teams, particularly those spanning national boundaries. She is co-editor with Sara Kiesler of the book Distributed Work (MIT Press). She also studies the sharing of expertise in organizations, focusing on the cognitive and motivational factors that inhibit sharing. Most recently, Pamela has begun conducting research on professional service robots in the work environment, examining how people make sense of them and how they affect work practices. She serves on the editorial board of *Organization Science*. Her research has appeared in *Organization Science, Research in Organizational Behavior, Journal of Applied Psychology, Journal of Experimental Psychology: Applied, Organizational Behavior and Human Decision Processes, Human-Computer Interaction, and the International Journal of Conflict Management.*