© Academy of Management Journal
2005, Vol. 48, No. 6, 1107–1123.

TEAM DIVERSITY AND INFORMATION USE

KRISTINA B. DAHLIN
University of Toronto

LAURIE R. WEINGART
Carnegie Mellon University

PAMELA J. HINDS
Stanford University

Educational and national diversity are proposed to influence work teams' information use differently, with educational diversity mainly enhancing information use and national diversity invoking social categorization, thus hindering information use. As expected, increasing educational diversity positively influenced the range and depth of information use for all except the most diverse teams we studied, but negatively influenced information integration. In contrast to our expectations, national diversity had curvilinear relationships with the range, depth, and integration of information use. Both types of diversity provided information-processing benefits that outweighed the limitations associated with social categorization processes.

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; although 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, which interfere with teams' ability to capitalize on increased information. In this study, we examined two types of diversity, educational and national. We posited that educational diversity allows groups to benefit from the informational diversity stemming from heterogeneity in education. Diversity in nationality, on the other hand, was viewed as likely to trigger social categorization processes and prevents teams from benefiting from potential informational advantages based on heterogeneous national backgrounds. We outline nonlinear 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. Although our results support the view that educational diversity enhances groups' information use, we also found—contrary to our expectations—that national diversity had 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 national 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 (Cohen & Levinthal, 1990; Katz, 1982). Consider top management team strategic decisions with effects that cascade down through an organization. Diversity in those teams allows them to tap a

This research was partially supported by National Science Foundation grant #IIS-9872996 to the third author. The authors would like to thank Terry Amburgey, Linda Argote, Joel Baum, Stéphane Côté, Martin Evans, and Sharmista Law for comments on earlier versions of this paper; Kathleen Carley for advice on the coding of textual data; You-Ta Chuang, Deborah Gibbons, Vanessa Hill, Rangarj Ramanujam, and Daniel Tzabbar for help with data coding; and the three anonymous reviewers for in-depth comments on methods and theory.

broader array of relevant information, increasing comprehension of the implications of each path that can be taken (Hambrick, Cho, & Chen, 1996; Hambrick & Mason, 1984). 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, it is necessary to understand the different types of diversity and how they relate to information use.

THEORY AND HYPOTHESES

In their review of the diversity literature, Williams and O'Reilly (1998) concluded that different types of diversity have different effects, some resulting primarily from changes in information processing and others, from social categorization. Our primary goal here was to understand how different types of diversity affect a team's use of information. We therefore considered 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-U.S. citizens in the American workforce has increased dramatically over the last decades (National Science Foundation, 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) representing distinct "thought worlds" (Dougherty, 1992). We expected the effects of educational diversity to be better explained by information-processing theories, because education influences the information, knowledge, and skills that people bring to a team (Williams & O' Reilly, 1998); the effects of diversity of nationality are better explained by social categorization theory (Earley & Mosakowski, 2000), according to which a shared group identity will derive from perceived similarity. In the next section, we define educational and national diversity. We then hypothesize how diversity is related to three aspects of information use: range, depth, and integration.

Educational and National Diversity in Teams

Educational diversity relates to the different sets of task-relevant skills, knowledge, and abilities team members possess as a function of their educational backgrounds. 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 their team is to do, which in turn influences what information they attend to and incorporate into decisions (Bunderson & Sutcliffe, 2002; Cohen & Levinthal, 1990). In this research, we focused on diversity in MBA student team members' *dominant* educational backgrounds (that is, their undergraduate majors). *Dominant educational diversity* is similar to what Bunderson and 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 functions, 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).

National diversity, in contrast, provides more information about social categories. Defined as the distribution and number of team members' national backgrounds, national 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 (National Science Foundation, 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 a 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 focused on the mechanism of information use in relation to educational and national diversity. We expected educational and national diversity to affect information use differently 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 decisions (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 treat both teams as information processors and information use as important parts of team performance.

We argue that team members' perspectives serve as a filter or conduit for potentially unique information that can be applied to their team 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 search 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 a 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 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 as to what information they have beyond information about hardware and, perhaps, manufacturing considerations.

Once collected, information must be considered in more *depth*. In-depth consideration 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 *integrate,* and act on the information, activities that occur in the fourth phase of collective cognition, the accommodation phase. In developing range and depth, and deciding how to integrate and organize 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 deeper knowledge of the implications of particular information for the decision taken.

The preceding discussion suggests that teams with education and nationality diversity will also exhibit differences in range, depth, and integration of information use (what Montoya-Weiss, Massey, and Song [2001] referred to as range, depth, and organization of information use). "Range" is the variety of information included in a team's rationale; "depth" captures the extent to which the arguments or issues raised in the rationale have been explored completely: and "integration" is the quality of the structuring of the rationale and the quality of the treatment of relationships 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, so an analysis results that is neither logical nor persuasive. A complete understanding of how education and nationality diversity are related to information use requires attention to all three dimensions of information use: range, depth, and integration.

How Team Diversity Impacts Information Use

We expected effects of team diversity on information use to be conditioned on the type of both diversity (educational versus national) and information use (range, depth, or integration). In the following sections, 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), ability to identify and make use of relevant information can be vital to success (Katz, 1982; Wheelwright & Clark, 1992). Cohen and Levinthal (1990) argued that a team's ability to access and use new information, what they labeled the team's "absorptive capacity," should be increased by including members with diverse backgrounds. Gaining expertise via formal education means acquiring a body of knowledge and—equally importantly—knowledge about where to find additional related information (Wegner, 1987). This knowledge influences the way individuals address a given problem and what new information they will notice and how they will perceive it. According to Bower and Hilgard (1981), making sense of and acquiring new knowledge are functions 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 category, including how they differ from one another), and links between the categories (i.e., the *integration* of knowledge that relates the categories to one another). Thus, the more previous knowledge individuals, teams, or organizations have, the easier it is for them to acquire new information and understand its value (Cohen & Levinthal, 1990; Wegner, 1987).

Diversity of team members' educational backgrounds will determine how a team will use information (Bantel & Jackson, 1989; Cohen & Levinthal, 1990; Pelled, Eisenhardt, & Xin, 1999). Range will be influenced by education diversity in that 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 whose task is designing an accounting system for a music group will engage a narrower range of information than a team with the same task composed of a software engineer, an accountant, and a musician. Assuming a relatively nonthreatening environment, the unique knowledge held by a diverse team should be used by the team (Edmondson, Bohmer, & Pisano, 2001). Thus, we predict that teams composed of members with diverse educations 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 a team (as in moderately diverse teams), team members are far more likely to express the information they hold, and the team is more likely to take the information into account (Wittenbaum & Stasser, 1996). A team whose members are highly diverse in their educational backgrounds may have so little overlap in shared information that members do not trigger each other's 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 is an inverted U-shaped curvilinear relationship between a team's educational diversity and its range *of information use: the range increases with increasing educational diversity but decreases at the highest levels of educational diversity.*

It might appear that our prediction contradicts Bunderson and Sutcliffe's (2002) findings that teams with members from a wide variety of functional areas (teams exhibiting dominant function diversity) engaged in less information sharing. However, we contend that dominant function 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 education diversity influences depth of information use up to a point (cf. Cohen & Levinthal, 1990: 135). Although information enters a 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 education diversity increases from low to moderate, a more diverse set of preexisting frameworks becomes 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 over more homogeneous ones, both with respect to familiar information (information that fits at least one team member's framework) and 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. These multiple relevant frameworks allow them to analyze a larger portion of information in depth. At the same time, we expected 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 deeper information use than teams with low educational diversity, since the former will have a broader set of frameworks allowing them to classify a larger set of issues as 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 is be an inverted U-shaped curvilinear relationship between educational diversity and the* depth *of information use: the depth increases with increasing diversity but decreases at 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 links are made between items of information (see Bower & Hilgard, 1981). When unique information comes from different team members, developing these links requires integrating knowledge. Knowledge integration occurs via interaction among team members that 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 high educational diversity exhibits lower* integration *of information than a team with low educational diversity.*

National diversity and information use. Although teams with national diversity may have different worldviews and perceptions that can positively influence information use (Choi, Nisbett, & Norenzayan, 1999; Goodman et al., 1990), we argue that national 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 theory suggests that individuals seek to bolster their in-group and derogate out-groups to enhance 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 as likely to be even more salient than culture, race, gender, and other status-determining traits (Earley & Mozakowski, 2000; Hambrick, Davison, Snell, & Snow, 1998). With nationality being such a salient characteristic, diversity in nationality might segment a team and interfere with team members' ability to work together effectively (Harrison, Price, & Bell, 1998; Tajfel, 1981; Turner, 1987).

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 national diversity have members that share national origin. We expected members with the same national origin to coalesce into subgroups, reinforcing one another and differentiating themselves from other subgroups in a team (Earley & Mozakowski, 2000; also Cramton & Hinds, 2005). We argue that nationality, being a salient social category, will likely cause the formation of strong subcategories in moderately diverse teams.

Groups that are highly diverse, in that (almost) all team members differ in national origin, and groups that are homogeneous, in 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, the members of a highly nationally homogeneous group will act as a cohort, and the members of a highly nationally heterogeneous group will attempt to establish a shared understanding of what it means to be a member of the group, developing a unique team identity (Earley & Mozakowski, 2000). These heterogeneous team members may derive their team identity from their diversity rather than from their similarities (Gibson & Vermeulen, 2003). Thus, we expected highly diverse teams, like homogeneous teams, to be more likely to coalesce into single groups rather than into distinct subgroups (Earley & Mozakowski, 2000; Gibson & Vermeulen, 2003). More specifically, we expected a U-shaped relationship between nationality diversity and information use. Previous research has demonstrated this form of relationship between national diversity and team performance in mature teams (Earley & Mosakowski, 2000) and between team heterogeneity and team learning behaviors when subgroups are strong (Gibson & Vermeulen, 2003), but ours is the first study to hypothesize this curvilinear effect on information use.

We argue that the social categorization and resulting subgroup formation that occurs in moderately diverse teams will interfere with the teams' ability to use information. Although teams with national diversity are likely to bring different perspectives and experiences to team encounters and efforts, 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 a team into identifiable subgroups (in-groups vs. out-groups) should interfere with its ability to access and use available information. We expected nationality diversity to interfere with a 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 subgroup 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 in splintered teams. These arguments are consistent with Earley and Mozakowski's (2000) finding that teams with low national 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 national diversity were effective at sharing their different perspectives. We therefore predict that teams with more national diversity will exhibit less range, depth, and integration of information, but only up to a point. At high levels of national diversity, we anticipate that teams will achieve increased range, depth, and coherence.

Hypothesis 4. There is a U-shaped curvilinear relationship between diversity of nationality and range *of information use: range decreases with increasing diversity, but increases at the highest levels of diversity of nationality.*

Hypothesis 5. There is a U-shaped curvilinear relationship between diversity of nationality and depth *of information use: depth decreases with increasing diversity, but increases at the highest levels of diversity of nationality.*

Hypothesis 6. There is a U-shaped curvilinear relationship between diversity of nationality and integration *of information use: integration decreases with increasing diversity, but increases at the highest levels of diversity of nationality.*

METHODS

Setting and Sample

As part of a seven-week introductory MBA organizational behavior (OB) course, 135 students randomly assigned to teams 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 contained 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 1 four-person team, 14 five-person teams and 4 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 several desirable qualities: (1) Highly motivated individuals whose grades depended upon team performance comprised the teams. (2) Teams varied on educational and national diversity while being relatively invariant on other diversity dimensions—among the 100 students, 17 were women and 2 were African-Americans; there was also little variance in age ($\bar{x}$ = 27, s.d. = 3.5 years) and work experience ($\bar{x}$ = 3.8, s.d. = 2.6 years). (3) Team membership persisted over two months. And (4) The teams had identical tasks, for which each received the same background information. These conditions provided a controlled, naturalistic situation in which 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, or consultants—both technical and managerial—are asked to evaluate competing bids or suggestions for businesses. Each of these tasks involves receiving a large and conflicting body of information that needs to be processed with respect to multiple perspectives (i.e., range is needed), processed in detail (i.e., depth is needed), and then integrated into a final report or verdict (i.e., integration is needed).

Measures

Educational diversity. Educational diversity was measured in terms of participants' undergraduate majors. We considered undergraduate major a good proxy for educational background because students in our sample were not far removed from their undergraduate studies, having less than four years of work experience on average. Students reported 32 unique undergraduate majors, the most common being economics; electrical, mechanical, and industrial engineering; computer science; and business administration. We coded down to the level of engineering subspecialties to be able to differentiate ten undergraduate engineering degrees. For example, we expected an industrial engineer to be more sensitive to issues surrounding manufacturing interfaces (such as conflict between sales and manufacturing, which was portrayed in one case) and expected mechanical engineers to react more to product design issues (one case discussed using an old product for new applications). To calculate diversity, we used Blau's (1977) index ($1 - \Sigma p_i^2$), where p_i is the fraction of team members with major i. Blau's index treats data as categorical; therefore we did not need to make any assumptions about how different majors were from one another. All teams in our sample were on the high end of Blau's index for educational diversity ($\bar{x}$ = 0.76, ranging from 0.56 to 0.83; see Table 1).

National diversity. National 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 they provided a reliable measure of nationality. We used country of citizenship for the remaining 10 students (8 Japanese and 2 U.S. citizens). The 100 participants came from 23 different countries, and 45 were non-U.S. ciitizens. Of the 45 non-U.S. students, 29 percent came from Europe, 27 percent from Japan, 20 percent from Asia excluding Japan, 9 percent from Latin America, 7 percent from the Caribbean, and 5 percent from Canada. The average number of nationalities represented in a team was three, and the range was between one and five (Blau's index: $\bar{x}$ = 0.55, ranging from 0.0 for a six-member team in which all members came from the United States to 0.8 for a five-person team in which all members came from different countries). All teams had at least one U.S. citizen, and in all teams but one, U.S. 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

TABLE 1
Descriptive Statistics and Correlations

Variable[a]	Mean	s.d.	2	3	4	5	6	7	8	9	10	11	12
1. Range	0.03	0.90											
2. Depth	0.09	0.99	.30*										
3. Organization	−0.01	0.95	.02	.44**									
4. Educational diversity	0.76	0.07	−.01	−.25†	−.18								
5. National diversity	0.55	0.17	−.07	−.04	.10	−.20							
6. Biculturals	0.51	0.69	−.02	−.04	−.00	.11	.63**						
7. English proficiency (TOEFL)	626.66	9.89	−.20	−.21	−.36*	.33*	−.16	.18					
8. Gender	0.88	0.88	−.01	.24	.00	−.12	.14	.02	.10				
9. Group size	5.11	0.49	.10	.09	−.14	−.01	.18	.30*	−.09	.35*			
10. Conflict	2.91	0.81	−.21	−.07	−.04	.11	.49**	.60**	.34*	.41**	.38*		
11. Delegation strategy	0.18	0.39	.06	−.00	−.39	.06	−.20	−.09	.36	.19	.25†	−.02	
12. Total units	136.51	37.82	.68**	.59**	.16	−.17	−.02	−.02	.34*	−.02	.11	−.13	.04

[a] English proficiency was coded as TOEFL score. Gender was the number of women on a team.
† $p < .10$
* $p < .05$
** $p < .01$

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) information in their analysis of the problems. We see application as an outcome of the information use process, a process that influences a final product (e.g., the overall quality of an analysis or a 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 write-up 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. A unit was defined as the expression of *a meaningful action* for an organization or person described in the case; it 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 percent of which were checked for unitizing reliability, which was high—that is, disagreement between the raters was very low (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) suggestive, or (3) reflected the outcome of a suggestion. We used only the descriptive/analytical units when calculating information use because we were interested in information analysis rather than in translation of information into future action. In the descriptive/analytic units, information from the case description was repeated, problems identified, and causal links between problems suggested. The interrater reliability for identifying descriptive/analytic units was high: Cohen's (1960) kappa varied between .77 and .86 across the cases, indicating excellent agreement (Fleiss, 1981). The second code dimension, topic, was case-specific and captured different content categories. For example, one case, which was concerned with goal alignment between organizational units, included categories such as "corporate-region goal alignment" and "incentive structure for sales personnel," and another case, which was 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 or absent in the analysis was good ($K = .64$).

Our measure of *range,* derived from the coding described above, counted the number of content categories in a group's analysis; Montoya-Weiss and her colleagues (2001) and Watson, Kumar, and Michaelsen (1993) have used this range measure, and Suedfeld, Tetlock, and Streufert's (1992) differentiation measure is also similar. If a topic was mentioned at least once, it was counted as present and coded as 1, and otherwise it was coded as absent (0). Code schemes for the different cases identified 40, 42, and 56 available topics respectively, and the maximum any team identified was 33, 37, or 38 topics. We standardized for the number of topics available to control for differences across cases, thus obtaining a measure that reflects a team's range of information use relative to that of other teams ($\bar{x}$ = 0.03, ranging from −1.80 to +1.79).

The measure of *depth* captured the average amount of information presented within each covered topic (Montoya-Weiss et al., 2001), measured by calculating the average number of descriptive/analytical units per topic identified in the case write-up. For example, if a group identified two topics, discussed one in five units, and discussed the other in nine units, the group's raw depth measure was (5+9)/2. 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 depth could be artificially inflated by verbosity. To make comparisons across cases possible, we also standardized the depth measure for each case ($\bar{x}$ = 0.09, ranging from −1.76 to +2.97).

Integration captured the consideration of relationships among diverse issues (Suedfeld et al., 1992; Watson et al., 1993). Three Ph.D. students, trained on a separate set of case write-ups and unaware of the hypotheses and the authors of the write-ups, were each provided with case-specific lists of possible problems/issues and trained to rate the quality of the integration of the analysis for each general issue. Criteria for quality, which we based on the measure "intrarelationships within relevant issues" from Montoya-Weiss et al. (2001) were whether arguments were well founded and whether a write-up contained causal links between topics raised within an issue. Integration was measured on a five-point scale. This measure was different from the others; depth and range were counts, but integration assessed how well the arguments across topics within an issue fit together. Interrater reliability was high (r = .88). We averaged ratings of the issues identified for each write-up to produce an overall measure of integration. As for the other information use measures, we standardized the integration measure for each case ($\bar{x}$ = −0.01, range −2.87 to +1.50).

Control Variables

We included seven control variables. Four variables addressed compositional characteristics of the teams other than national and educational diversity: number of bicultural 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.

Bicultural members. Many of the students who were not U.S. citizens had received their undergraduate degrees in the United States. We refer to this group as "biculturals" because they had significant life experiences in multiple cultures.[1] Non-U.S. students with undergraduate experience in the United States should be more accustomed to and more likely to adopt U.S. norms and customs than non-U.S. students without such experience. As a result, other team members should find it more difficult to cleanly assign such a person to a social category related to nationality since, in some ways, he or she belongs to two: one by virtue of birth and a second by virtue of their U.S. undergraduate educational experiences. Because these biculturals do not cleanly reflect a non-U.S. nationality, their presence could dilute the effects of national diversity. In our sample, biculturals represented 23 percent of the non-U.S. team members. Teams had between zero and two bicultural team members, with eight teams having none, nine having one, and two having two bicultural team members.

English proficiency. We controlled for American English language proficiency using teams' average scores on TOEFL (Test of English as a Foreign Language). This control helped rule out the explanation that findings related to national diversity could be the result of highly diverse teams having lower English proficiency. TOEFL 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 U.S. colleges and universities. Because we needed a team-level measure of English proficiency, and TOEFL scores did not exist for the native English speakers in our sample (they were not required to take the test), we imputed normally distributed data based on a 6 percent higher average score and a standard deviation 13 percent lower for the native English speakers than for the nonnative speakers (TOEFL score = 651.47, s.d. = 27.00). We chose the mean and standard deviation values on the basis of observed differences in GMAT scores between native and nonnative speakers, as the Educational Testing Services (2004) states that results on the TOEFL test should be be similar to those on the language portion of two other widely used tests, the GRE and GMAT (Educational Test-

[1] We recognize that these people may not be bicultural in 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).

ing Service, 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 the 19 teams were all male, but there were no all-female teams (the maximum number of women on a single team was three).

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 that size might therefore be driving any diversity effects.

Team conflict. Team conflict was assessed to rule out the possibility that diversity effects (positive or negative) might be a consequence of a high level of conflict in a team (e.g., Pelled et al., 1999). We measured team conflict (five items, $\alpha = .77$; 1 = "low conflict" to 5 = "high conflict") at the end of the semester, asking students to rate the level of conflict during the entire seven-week course. Of 94 students who completed the questionnaire containing this measure, 30 failed to identify their team, leaving us 64 (68%) usable questionnaires ($\bar{x} = 3$ questionnaires/team). For teams with at least two members answering the questionnaire, we constructed a group mean and obtained a within-group agreement coefficient ($r_{wg(j)}$; James, Demaree, & Wolf, 1984) of .66. 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 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 only one individual had produced the case write-up 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 the following control variables but did not include them in analyses 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 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 links between issues. Length of case (total units) was associated with range and depth, but not with integration. This finding 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 generalized least squares (GLS) regression analyses for panel data with an autoregressive correction (AR1; Greene, 2000). This formulation corrected for multiple observations per group that by definition were *not* independent, allowing us to use the full set of 45 cases. More specifically, the panel data formulation handled data with repeated observations (i.e., multiple cases per team) by assigning a group fixed effect that controlled for aspects of teams not captured by our measures (for instance, groups choosing different task strategies or different leadership models). The GLS formulation also allowed for autocorrelation within panels and heteroscedasticity across panels. The autocorrelation correction controlled for dependencies in residuals across the different cases, and the heteroscedasticity correction compensated for the possibility that our models might explain more variance for one case than for another. This capability allowed us to account for the fact that the cases differed on complexity, length, issue salience, and more.

Range of Information

We predicted that educational diversity would positively influence range of information use, but only to a point (Hypothesis 1), and that national diversity would negatively influence it, but again, only to a point (Hypothesis 4). Regression results showed both significant, positive, linear ($Z = 76.90$, $p < .01$) and negative, curvilinear ($Z = -52.50$, $p < .01$) relationships for educational di-

[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 (Educational Testing Service, 2004); and (2) the average score and standard deviatation of nonnative 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.

versity (see Table 2, model 2), suggesting a positive but inverted U-shaped slope, supporting Hypothesis 1. 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 Hypothesis 4.

Comparing the effect of educational diversity with that of national diversity, we found that the curvilinear effect of educational diversity was significantly greater than the curvilinear effect of national diversity ($\chi^2[1] = 21.30$, $p < .01$). See Figures 1a and 1b for plots of the predicted values of range of information use as a function of diversity.

Depth of Information

We hypothesized that educational diversity would have an inverted U-shaped curvilinear effect on depth of information use (Hypothesis 2) and that national diversity would have a U-shaped curvilinear effect on depth of information use (Hypothesis 5). 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 -63.29 for educational diversity squared, both $p < .01$; see model 4). Hypothesis 5 was not supported in that the relationship between national diversity and depth took the form of an inverted U ($Z = 8.41$ for national diversity and -8.80 for national diversity squared, both $p < .05$; see model 4). Again, the effect of educational diversity was stronger than the effect of national diversity ($\chi^2[1] = 10.03$, $p < .01$). 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 (Hypothesis 3) and a U-shaped curvilinear effect of national diversity (Hypothesis 6) on integration of information. Model 6 (Table 2) shows support for Hypothesis 3 (educational diversity: $Z = -2.14$, $p < .05$) (see Figure 1a).[3] National diversity, however, was found to have a positive ($Z = 11.09$, $p < .01$) and inverted U-shaped curvi-

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

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

	Range of Information Use		Depth of Information Use		Integration of Information	
	1	2	3	4	5	6
Variables[a]	Control Model	Full Model	Control Model	Full Model	Control Model	Full Model
Constant	2.66 (5.84)	−22.06 (8.43)***	−0.54 (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)**		
National diversity		−6.62 (1.91)**		8.41 (4.29)*		11.09 (3.68)**
National diversity squared		6.34 (1.88)**		−8.80 (4.32)*		−11.23 (3.72)**
Biculturals	0.05 (0.16)	0.27 (0.13)*	0.03 (0.11)	0.37 (0.20)†	−0.00 (0.16)	0.16 (0.18)
English proficiency	−0.08 (0.08)	−0.10 (0.07)	−0.05 (0.08)	0.18 (0.10)†	−0.25 (0.10)*	−0.21 (0.11)†
Gender	0.03 (0.08)	−0.08 (0.06)	0.32 (0.10)**	0.28 (0.13)*	0.25 (0.10)*	0.30 (0.11)**
Size	0.11 (0.17)	0.24 (0.13)†	0.31 (0.27)	0.54 (0.25)*	−0.24 (0.22)	−0.40 (0.20)*
Conflict	−0.24 (0.10)*	−0.40 (0.10)**	−0.09 (0.12)	−0.20 (0.10)†	−0.03 (0.15)	0.19 (0.17)
Delegation strategy	0.14 (0.20)	0.02 (0.17)	0.08 (0.19)	−0.28 (0.18)	−0.94 (0.27)**	−0.74 (0.31)*
Total units	0.16 (0.02)**	0.15 (0.01)**	0.14 (0.02)**	0.14 (0.02)**	0.05 (0.02)*	0.05 (0.03)*
Log-likelihood chi-square	−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

[a] The variables for total units and English proficiency were divided by 10 to scale coefficients and standard errors.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

FIGURE 1a
Educational Diversity and Information Use

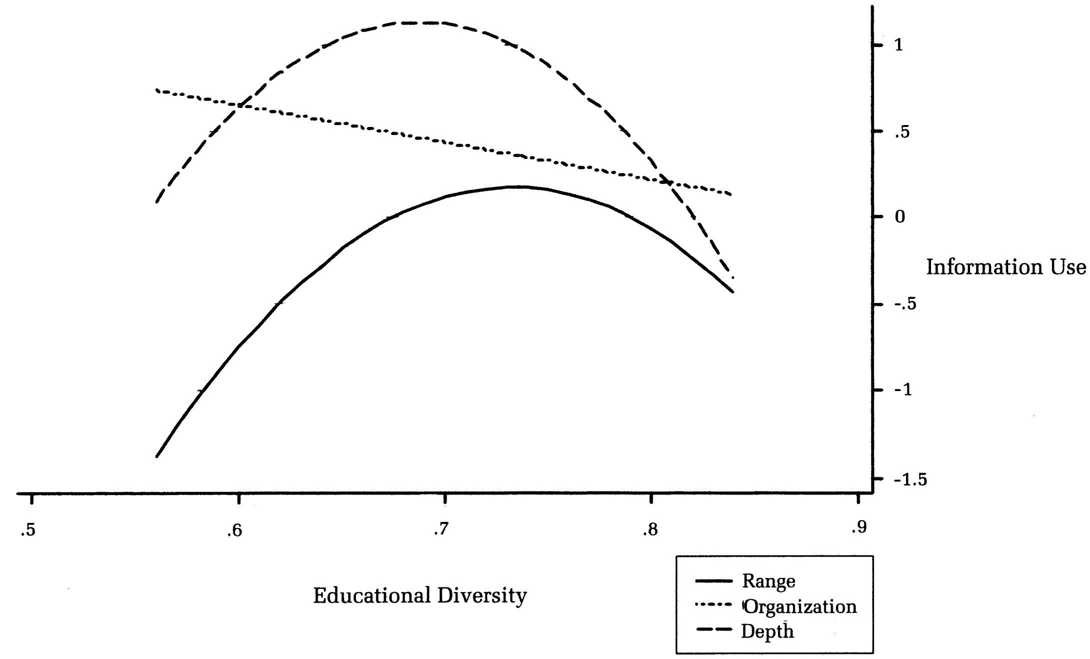
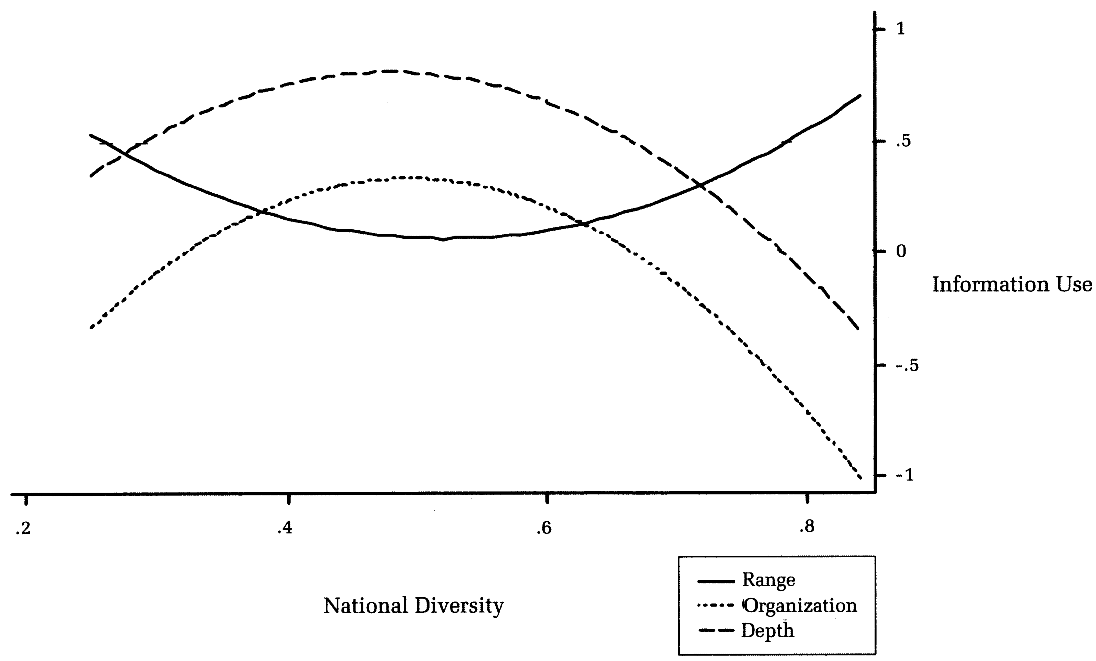


FIGURE 1b
National Diversity and Information Use



linear effect (Z = −11.23, $p < .01$) on integration (see Table 2, model 6, Figure 1b). Thus, Hypothesis 6 was not supported. As before, the effect of educational diversity was stronger than that of national diversity ($\chi^2[1] = 9.68$, $p < .01$).

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 teams themselves (size, proportion of biculturals, and members' English proficiency and gender), 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 national) in small teams influence information use in different ways. 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 it has been previously believed to be and that treating information use as a single construct may obscure important differences.

Diversity of education had stronger effects on the range, depth, and integration of information use than did nationality. This finding is not surprising, and is perhaps comforting, in that diversity dimensions such as education mirror a true difference in perceptions and knowledge and have direct relevance for a task at hand, while nationality has less direct relevance to tasks. 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-shaped curvilinear effects on the range and depth of information use and a negative effect on integration, and national diversity had a U-shaped curvilinear relationship with range. But, contrary to predictions, national diversity had an inverted U-shaped relationship with depth and, to a lesser degree, an inverted U-shaped relationship with integration, suggesting benefits to diversity of nationality we did not anticipate (see Figures 1a and 1b for illustrations of the relationships).

Our results point to ways that educational diversity can both help and hinder teams' ability to use information. In this study, the more diverse teams used broader ranges 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 exhibited more depth of information use; however, at the highest levels of diversity, teams returned to relatively shallow analyses, equivalent in depth to those of the 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 Cohen and Levinthal's argument concerned 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 connect topics within issues. Drawing connections requires knowledge of each relevant content area. In that educationally diverse teams have distributed knowledge of content, they have more difficulty making links because they have to bridge from one team member to another. In sum, educational diversity can both help and hinder a team's ability to use information. Some diversity in educational background will increase the amount of information available to a team, yet too much makes it difficult to access, explore, and link this information. In situations in which the integration of information is of great importance, special attention and time need to be allocated to the integration aspect of group cognition (Gibson, 2001).

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

National diversity had unanticipated benefits on information use and, although social categorization resulting from national 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 great depth or to use that information in a coherent way. These findings contradict those of Earley and Mozakowski (2000), who found that moderate levels of national diversity interfered with information use. In fact, moderate nationality diversity stimulated depth and 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 national 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 (depth). Drawing on our results, we conjecture that social categorization processes may mainly affect the accumulation phase, where they disrupt the introduction of new ideas into a 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 deeper processing and better linking of topics. This is not to say that social categorizations become irrelevant at later stages, but rather, that different ways of thinking about the information accumulated by a group may outweigh the polarizing effects of social categorization. A side benefit of a group's identifying a narrow range of information during the accumulation phase is that it increases team ability to process that information, because more resources are available. As Gibson (2001) argued, 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 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 one would also expect processing at later stages (interaction, examination, and accommodation) to benefit from national diversity as social categorization along national boundaries diminishes. This reasoning 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 substitution 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 their tasks (Cohen & Levinthal, 1990; Tushman & Scanlan, 1981) that can best be capitalized on by moderately 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 because issues compete for attention when team members are diverse. Finally, teams that need to make complex links between unique information categories (e.g., top management teams) might suffer when expertise diversity is high but benefit when nationality diversity is moderate to high. While dispersal of information among different experts in the group might interfere with a 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, undoubtedly as a consequence of team processes. Our results suggest that the effects of diversity on information use occur regardless of the level of conflict or the presence of biculturals on a team. As we suspected, bicultural team members, or members who have experience in two countries or cultures, help a team capitalize on its diversity by increasing the range and depth of its information use. Conflict, in contrast, interfered with range and interfered somewhat with depth of information use.

There are several limitations to the study. First, our participants were students. Although using a student sample provides many advantages in terms of control, we recognize that student teams operate in a different context than organizational teams, whose organizations have a stake in the teams' work. Having said that, we note that academic institutions have much at stake regarding how to integrate international students into student work teams: In *BusinessWeek's* 2003 top 30 U.S. "B-schools," non-U.S. citizens accounted for 34.3 of the average MBA class (*BusinessWeek,* 2003). Another key difference between student teams and teams within organizations concerns time horizon. Absorptive capacity is claimed to have cumulative properties (Cohen & Levinthal, 1990); such accumulation would make 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 them. 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 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. Including teams with low education diversity would have provided a more complete picture of the form of education diversity's 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 national 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 are from the United States, as opposed to the national origins 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 in such a way that attributes invoking social categorization (e.g., nationality) are cross-cut with attributes that promote information processing (e.g., expertise).

REFERENCES

Alderfer, C. P., & Smith, K. K. 1982. Studying intergroup relations embedded in organizations. ***Administrative Science Quarterly,*** 27: 35–65.

Bantel, K., & Jackson, S. 1989. Top management and banking: Does the composition of the top team make a difference? ***Strategic Management Journal,*** 10: 107–124.

Blau, P. 1977. ***Inequality and heterogeneity: A primitive theory of social structure.*** New York: Free Press.

Bower, G., & Hilgard, E. 1981. ***Theories of learning.*** Englewood Cliffs, NJ: Prentice-Hall.

Bunderson, J. S., & Sutcliffe, K. M. 2002. Comparing alternative conceptualizations of functional diversity in management teams: Process and performance effects. ***Academy of Management Journal,*** 45: 875–893.

BusinessWeek. 2003. MBA insider, student profile and school tuition tables. www.businessweek.com/bschools/ozwebsite.

Cagan, J., & Vogel, C. M. 2002. ***Creating breakthrough products: Innovation from product planning to program approval.*** Upper Saddle River, NJ: Prentice-Hall.

Choi, I., & Nisbett, R. E., & Norenzayan, A. 1999. Causal attribution across cultures: Variation and universality. ***Psychological Bulletin,*** 125: 47–63.

Cohen, J. 1960. A coefficient of agreement for nominal scales. ***Educational and Psychological Measurement,*** 20: 37–46.

Cohen, W., & Levinthal, D. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative Science Quarterly,*** 35: 128–152.

Cox, T. H. 1993. ***Cultural diversity in organizations.*** San Francisco: Berett-Koehler.

Cramton, C. D., & Hinds, P. J. 2005. Subgroup dynamics in internationally distributed teams: Ethnocentrism or cross-national learning? In B. M. Staw & R. Sutton (Eds.), ***Research in organizational behavior,*** vol. 26: 231–264. Greenwich, CT: JAI.

Dougherty, D. 1992. Interpretive barriers to successful product innovation in large firms. ***Organization Science,*** 3: 179–202.

Earley, P. C., & Gibson, C. B. 2002. ***Multinational work teams: A new perspective.*** Mahway, NJ: Erlbaum.

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

Edmondson, A. C., Bohmer, R. M., & Pisano, G. P. 2001. Disrupted routines: Team learning and new technology implementation in hospitals. ***Administrative Science Quarterly,*** 46: 685–716.

Educational Testing Service. 2004. ***Test and score manual supplement.*** Princeton, NJ: Educational Testing Service.

Edwards, W. 1954. The theory of decision making. ***Psychological Bulletin,*** 51: 380–417.

Erez, M., & Earley, C. P. 1993. ***Culture, self-identity, and work.*** New York: Oxford Press.

Fleiss, J. L. 1981. ***Statistical methods for rates and proportions*** (2nd ed.). New York: Wiley.

Gibson, C. 1996. Do you hear what I hear? A framework for reconciling intercultural communication difficulties arising from cognitive styles and cultural values. In M. Erez & P. C. Earley (Eds.), ***New perspectives on international industrial organizational psychology:*** 335–362. San Francisco: Jossey-Bass.

Gibson, C. 2001. From knowledge accumulation to accommodation: Cycles of collective cognition in work groups. ***Journal of Organizational Behavior,*** 22: 121–134.

Gibson, C., & Vermeulen, F. 2003. A healthy divide: Subgroups as a stimulus for team learning behavior. ***Administrative Science Quarterly,*** 48: 202–239.

Gibson, C., & Zellmer-Bruhn, M. 2001. Metaphors and meaning: An intercultural analysis of the concept of teamwork. ***Administrative Science Quarterly,*** 46: 274–303.

Goodman, P. S., Ravlin, E. C., & Schminke, M. 1990. Understanding groups in organizations. In L. L. Cummings & B. M. Staw (Eds.), ***Leadership, participation, and group behavior:*** 323–385. Greenwich, CT: JAI Press.

Greene, W. H. 2000. ***Econometric analysis*** (4th ed.). Upper Saddle River, NJ: Prentice-Hall.

Guetzkow, H. 1950. Unitizing and categorizing problems in coding qualitative data. ***Journal of Clinical Psychology,*** 6: 47–58.

Hambrick, D., Cho, T., & Chen, M. 1996. The influence of top management team heterogeneity on firms' competitive moves. ***Administrative Science Quarterly,*** 41: 659–684.

Hambrick, D. C., Davison, S. C., Snell, S. A., & Snow, C. C. 1998. When groups consist of multiple nationalities: Toward a new understanding of the implications. ***Organizational Studies,*** 19: 181–205.

Hambrick, D., & Mason. 1984. Upper echelon: The organization as a reflection of its top managers. ***Academy of Management Review,*** 9: 193–206.

Hinsz, V. B., Tindale, R. S., & Vollrath, D. A. 1997. The emerging conceptualization of groups as information processors. ***Psychological Bulletin,*** 121: 43–64.

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

James, L. R., Demaree, R. G., & Wolf, G. 1984. Estimating within-group interrater reliability with and without response bias. ***Journal of Applied Psychology,*** 69: 85–98.

Katz, R. 1982. The effects of group longevity on project communication and performance. ***Administrative Science Quarterly,*** 27: 81–104.

Kilduff, M., Angelmar, R., & Mehra, A. 2000. Top management-team diversity and firm performance: Examining the role of cognitions. ***Organization Science,*** 11(1): 21–34.

Krauss, R. M., & Fussell, S. R. 1990. Mutual knowledge and communicative effectiveness. In J. Galegher, R. E. Kraut, & C. Egido (Eds.), ***Intellectual teamwork:*** 111–145. Hillsdale, NJ: Erlbaum.

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

Montoya-Weiss, M. M., Massey, A. P., & Song, M. 2001. Getting it together: Temporal coordination and conflict management in global virtual teams. ***Academy of Management Journal,*** 44: 1251–1262.

National Science Foundation. 1999. ***How much does the U.S. rely on immigrant engineers?*** (Division of Science Resources studies issue brief). http://www.nsf.gov/sbe/srs/issuebrf/sib99327.htm (accessed Feb. 14, 2004).

Pelled, L., Eisenhardt, K., & Xin, K. 1999. Exploring the black box: An analysis of work group diversity, conflict, and performance. ***Administrative Science Quarterly,*** 44: 1–28.

Sole, D., & Edmondson, A. 2002. Situated knowledge and learning in dispersed teams. ***British Journal of Management,*** 13: S17–S34.

Stasser, G., & Titus, W. 1985. Pooling of unshared information in group decision-making: Biased information sampling during discussion. ***Journal of Personality and Social Psychology,*** 48: 1467–1478.

Suedfeld, P., Tetlock, P. E., & Streufert, S. 1992. Conceptual/integrative complexity. In C. P. Smith (Ed.), ***Motivation and personality: Handbook of thematic content analysis:*** 393–400. New York: Cambridge University Press.

Tajfel, H. 1981. ***Human groups and social categories: Studies in social psychology.*** Cambridge, UK: Cambridge University Press.

Educational Testing Service. 2004. ***Test and score man-***

ual supplement. Princeton, NJ: Educational Testing Service.

Turner, J. 1987. ***Rediscovering the social group: A social categorization theory.*** Oxford, UK: Blackwell.

Tushman, M., & Scanlan, T. J. 1981. Boundary spanning individuals: Their role in information transfer and their antecedents. ***Academy of Management Journal,*** 24: 289–305.

Watson, W. E., Kumar, K., & Michaelsen, L. K. 1993. Cultural diversity's impact on interaction process and performance: Comparing homogeneous and diverse task groups. ***Academy of Management Journal,*** 36: 590–602.

Wegner, D. 1987. Transactive memory: A contemporary analysis of the group mind. In B. Mullen & G. R. Goethals (Eds.), ***Theories of group behavior.*** New York: Springer-Verlag.

Wheelwright, S. J., & Clark, K. 1992. ***Revolutionizing product development: Quantum leaps in speed, efficiency, and quality.*** New York: Free Press.

Williams, K., & O' Reilly, C. 1998. Demography and diversity in organizations: A review of 40 years of research. In B. M. Staw & L. L. Cummings (Eds.), ***Research in organizational behavior,*** vol. 20: 77–140. Greenwich, CT: JAI.

Wittenbaum, G. M., & Stasser, G. 1996. Management of information in small groups. In J. L. Nye & A. M. Brower (Eds.), ***What's social about social cognition? Research on socially shared cognition in small groups:*** 3–28. Thousand Oaks, CA: Sage.

Zellmer-Bruhn, M. E., Maloney, M. M., Bhappu, A. D., & Salvador, R. O. 2004. ***Beyond demographic heterogeneity: An exploration of perceived similarity in teams.*** Working paper, Southern Methodist University, Dallas.

Kristina B. Dahlin *(dahlin@rotman.utoronto.ca)* is an assistant professor in strategy and organization at the Joseph L. Rotman School of Management, University of Toronto. Her Ph.D. is in organizational behavior and theory and is 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. Parallel interest areas are the role of independent inventors as well as the measurement and evolution of technology.

Laurie R. Weingart *(weingart@cmu.edu)* 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.

Pamela J. Hinds *(phinds@stanford.edu)* is an associate 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 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.