Paper to be presented at the DRUID 2011

on

INNOVATION, STRATEGY, and STRUCTURE -
Organizations, Institutions, Systems and Regions
at
Copenhagen Business School, Denmark, June 15-17, 2011

Deep Under the Surface: The Effects of Diversity and Depth of Analysis on Group Creativity

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Abstract

We test two factors that jointly determine creativity in groups: Diversity and depth of analysis. We argue that depth of analysis moderates the effect of diversity on creativity in that less diverse groups that engage in deep analysis will apply a more novel set of ideas, since group members with similar knowledge are better able to explore and understand nuanced differences in each other?s deep knowledge. Our findings support the theory to show that the least creative groups are diverse groups that engage in deep analysis

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Key words: creativity, diversity, depth of analysis

1. Introduction

Creativity is the process from which innovations are borne (Amabile, 1988; Taylor & Greve, 2006). By defining creativity as the generation and application of novel and useful ideas (Woodman, Sawyer, & Griffin, 1999), both researchers and practitioners alike have argued that diversity in groups facilitates creativity because more diverse groups can tap greater differences in thinking than less diverse groups. How groups tap these greater differences at their disposal, however, can negatively affect creativity. For instance, creativity is hampered when differences in thinking produces unconstructive conflict, such as group members perceiving critical disagreements as personal attacks on their intelligence. Indeed, a recent meta-analysis suggests that it is only in the presence of moderators - like support for innovation and external communication - that diversity in groups facilitates the constructive expression of differences in thinking that leads groups to creativity (Hülsheger, Anderson, & Salgado, 2009; Mannix & Neale, 2005). Moreover, given that creativity presents the dual demand of generating novel ideas *and* applying these novel ideas in useful ways, the research to date, while providing important insights about novel idea generation, has revealed little about moderators responsible for the application of novel ideas in useful ways.

We address this limitation by considering how groups apply their novel ideas in useful ways. We draw from research on information processing in groups (Dahlin, Weingart, & Hinds, 2005; Hinsz, Tindale, & Vollrath, 1997) to hypothesize that groups will be more creative the more they engage in deep analysis, where depth of analysis is defined as the amount of information used to analyze a problem. Furthermore, we challenge the widely held belief that diverse groups are more creative than less diverse groups. We reason that when less diverse groups engage in deep analysis, they are better able to tap and integrate differences in deep knowledge to apply novel ideas in useful ways. To directly study this link between depth of analysis and creativity, we depart from the commonly used methods of studying product development (e.g. Keller, 2001; Sethi, Smith, & Park, 2001; Sutton & Hargadon, 1996). Instead, we studied how MBA groups apply their novel ideas by analyzing case write-ups.

In sum, our paper makes three distinct contributions: First, we go beyond idea generation and focus on how groups apply their novel ideas. Second, by showing that less diverse groups can be more creative, we provide an alternative way to link diversity to creativity in that diversity in terms of deep knowledge is more important than diversity in knowledge per se. Third, analyzing MBA group case write-ups allows us to directly study how groups apply ideas which extends our understanding of group creativity beyond product development to other organizational contexts; such as situations in which groups are asked to develop policies, or consultants asked to evaluate competing bids or suggestions for companies.

2. Group Diversity and Creativity

Diversity is defined as “any attribute that another person may use to detect individual differences” (Williams & O’Reilly, 1998: p. 81). As such, diversity in groups has been categorized in a variety of ways, including age, gender, ethnicity, nationality, values, attitudes, expertise, and educational background. The effects of these diversity categories on group creativity have typically been examined through an information-processing approach showing that differences between group members benefit creativity when creativity is measured as the generation of novel and useful ideas (Keller, 2001; Sethi et al., 2001; Sutton & Hargadon, 1996; Taylor & Greve, 2006). The information-processing approach asserts that diversity provides exposure to different backgrounds, networks, information, and skills, which should facilitate group creativity despite the coordination problems the group will face (Mannix & Neale, 2005). For example, expertise diversity provides exposure to differences in knowledge and perspectives, all of which present a variety of ideas from which group members can build off each other's ideas to generate a stream of possible new ideas (Sutton & Hargadon, 1996). However, research to date also suggests that the creative potential from diversity attributes like expertise and educational background is only realized when moderating processes such as communication and information exchange are controlled for (Hülsheger et al., 2009; Mannix & Neale, 2005). Thus, while current research has provided insights into how diversity affects the generation of novel ideas, we know little about the moderating processes that affect the application of novel ideas in useful ways.

In this paper, we extend our understanding of the link between diversity and creativity by considering diversity and depth of analysis as two factors having a joint impact on group creativity. Diversity determines the potential for creativity because it *provides access* to the pool of diverse knowledge from which groups can potentially generate novel ideas. However, depth of analysis – a moderator – determines *whether and how* novel ideas are generated and applied as useful solutions (Figure 1).

Insert Figure 1 about here.

2.1. Diversity and the Potential for Creativity

Traditionally, diversity has been linked to creativity because diversity allows a group access to, and use of, a larger and more varied knowledge base than that available to a less diverse group (Keller, 2001; Williams & O'Reilly, 1998). This larger and more varied knowledge base impacts groups' generation of new ideas with the expectation that more diverse groups generate more creative solutions (McGlynn, McGurk, Effland, Johll, & Harding, 2004; Paulus & Yang, 2000; Sutton & Hargadon, 1996). Alternatively, a larger and more varied knowledge base also allows a group to consider combining a greater variety of different pieces of information and, therefore, the group is more likely to discover a novel combination as a suitable idea (Dunbar, 1997; Finke, Ward, & Smith, 1992; Hargadon & Bechky, 2006). Either way, diversity in groups is linked to creativity because more diversity provides greater exposure to differences in knowledge than less diversity does.

We suggest, however, that research to date has overlooked that less diverse groups also provide exposure to differences in thinking. For instance, imagine a group of management consultants who all received their undergraduate education in engineering from the same university. While this group is prima facie a less diverse group in that they all share the same general knowledge in engineering (calculus, engineering problem-solving methods, linear algebra, etc.), each member has a unique knowledge stock in that they do not overlap in terms of deep knowledge in engineering. These differences in deep knowledge accumulate from each individual's respective interests and subjective experiences with engineering. While one group member may have written an undergraduate thesis in fluid dynamics in engineering, another might have written an undergraduate thesis in thermal dynamics, and yet another might have written a thesis on materials engineering, and so on. In addition to acquiring deep differences from undergraduate experiences, each consultant would acquire further differences in deep knowledge from subjective work experiences. Thus, while a group of consultants who all have educational backgrounds in engineering certainly looks less diverse compared to a group of consultants with a mix of educational backgrounds in economics, law, and architecture, a group of engineers can expose group members to differences in deep knowledge such as personal know-how, tricks-of-the-trade, and tacit knowledge.

Moreover, members of a less diverse group have the domain-specific expertise to tap the group's differences in deep knowledge to effectively build-off each other's ideas to generate new ideas. In contrast, even though diverse groups certainly have differences in deep knowledge, members of a diverse group do not have the required domain-specific expertise to access and know-how to use these differences. Therefore, they are less likely to generate new ideas based on differences in deep knowledge. For example, collaboration between Apple computer product designers with jelly-bean makers on how to manufacture colored plastic to be vibrant-looking involves the exchange of different but non-deep knowledge on coloring techniques compared to the exchange of deep knowledge differences on hacking protocols between two hackers collaborating to solve source code bugs within an open source community.

Thus, given that creativity "requires the application of deep knowledge because individuals must understand a knowledge domain to push its boundaries with any nontrivial likelihood of success" (Taylor & Greve, 2006: p. 725; Sternberg & O'Hara, 2000), we suggest that less diverse groups have the potential to be more creative to the extent that they are able to tap differences in deep knowledge to generate novel ideas *and* effectively apply these novel ideas in useful ways when developing a solution, In fact, in finding a weak association between diversity and creativity, recent reviews and meta-analyses call for research to identify moderators to explain the link between diversity and creativity (Hülsheger et al., 2009; Mannix & Neale, 2005). To this end, we propose that the extent to which a group engages in deep analysis determines whether differences in deep knowledge are accessed to generate and apply novel ideas in useful ways (Dahlin et al., 2005).

Drawing on the concept of groups as information processers (Hinsz et al., 1997), we define depth of analysis as the amount of information groups use to analyze a problem (Dahlin et al., 2005). We theorize that with greater depth of analysis, less diverse groups will be more creative than diverse groups for two reasons. First, less diverse groups will generate more novel ideas than heterogeneous groups because they are better able to tap differences in deep knowledge to generate novel ideas. Second, less diverse groups will be more effective at applying novel ideas in useful ways than diverse groups because they are better positioned to detect and fix errors in application. Thus, we will be able to provide insights into the circumstances under which less diverse groups are more creative than diverse groups and vice versa.

2.2. Realizing Creative Potential: The Moderating Effect of Depth of analysis

We suggest that as less diverse groups engage in increasing amounts of deep analysis the more novel the ideas they will generate, compared to the ideas generated by more diverse groups, By engaging in deep analysis, less diverse groups are able to generate novel ideas based on differences in deep knowledge. Of course, given that diverse groups have a greater non-overlap in knowledge compared to less diverse groups, less diverse groups have a smaller and less varied pool of knowledge to work with to generate novel ideas. However, we argue that by using larger amounts of information to analyze a problem, i.e. high levels of engagement in deep analysis, less diverse groups will go beyond their overlapping non-deep knowledge to tap non-overlapping knowledge which consists of differences in deep knowledge. In contrast, because diverse groups have to engage in high levels of deep analysis to deal with the difficult challenge of using differences in non-deep knowledge, this reduces the likelihood of tapping into differences in deep knowledge. That is, while there is a greater degree of knowledge non-overlap within diverse groups compared to less diverse groups, less diverse groups use differences in deep knowledge to generate new ideas whereas diverse groups use differences in non-deep knowledge to generate new ideas. By engaging in deep analysis to use differences in deep knowledge, less divers groups will be able to avoid the tendency of one team member to inhibit or block the ideas of another member (e.g. Paulus & Yang, 2000). In this way, less diverse groups can generate more novel ideas than diverse groups by pushing the limits of their thinking on a problem by using differences in deep knowledge.

We further suggest that since creativity depends on the application of deep knowledge to push the boundaries of a domain (Taylor & Greve, 2006), less diverse groups that engage in deep analysis will be more effective at applying novel ideas in useful ways than diverse groups for three reasons. First, recent theory suggests that expertise in groups can results in groups losing flexibility in problem-solving, adaptation, and creative idea generation (Dane, 2010). Given that expertise reflects high levels of stability in knowledge schemas (ibid.), we suggest that less diverse groups are equipped with more appropriate expertise and skills than diverse groups to overcome the cognitive resistance of expertise. For example, less diverse groups have the expertise to be more critical in identifying errors and good ideas than diverse groups (e.g. Lee & Cole, 2003). Less diverse groups are also better positioned to frame these errors in a way that is more convincing and effective to think differently to apply novel ideas in useful ways. This is because less diverse groups are better positioned to offer more effective know-how to apply or fix the identified errors when applying a group's solution (Lee & Cole, 2003).

Second, less diverse groups are also more effective at developing a good understanding of each member's true skills and expertise (Cohen & Levinthal, 1990). This understanding facilitates the effective communication of differences in deep knowledge such that each group member is better positioned to absorb and use these differences (Levin & Cross, 2004; Walker, 1985). That is, less diverse groups should have a greater absorptive capacity than diverse groups because (Reagans & McEvily, 2003: p. 243):

> one of the most important ways that people learn new ideas is by associating those ideas with what they already know. As a result, people find it easier to absorb new ideas in areas that they have some expertise in and find it more difficult to absorb new ideas outside of their immediate area of expertise. An implication is that it is easier for knowledge to transfer from the source to the recipient when the source and the recipient have knowledge in common. Consequently knowledge is more likely to be transferred between people with similar training and background characteristics.

For example, a microbiologist is more likely to be able to effectively implement differences in deep knowledge received from another microbiologist – as opposed to differences in deep knowledge received from a chemical engineer – in useful ways to solve important microbiology problems. In contrast, one might argue that diverse groups characterized by long-term collaborations can also develop a similarly effective absorptive capacity in the transfer of deep knowledge (e.g. Hansen, 1999; Sosa, 2010). However, given the same long-term collaboration, less diverse groups should still have an advantage over diverse groups because less diverse groups draw from a shared pool of expertise and techniques to communicate and exploit differences in deep knowledge. Thus, we expect that when less diverse groups engage in deep analysis, they will be more effective at applying novel ideas in useful ways than diverse groups.

As we have argued, we expect the two factors of interest to us – diversity and depth of analysis – to jointly affect group creativity in terms of generating and applying novel ideas in useful ways (see Figure 1). Based on the reasoning that less diverse groups that engage in deep analysis can access differences in deep knowledge to generate novel ideas and have the right expertise to effectively apply these ideas in useful ways, we hypothesize that:

HYPOTHESIS 1. Depth of analysis is positively correlated to creativity and leads to greater creativity in less diverse groups than in diverse groups.

More specifically, we are interested in how the interaction plays off for high-versus-low values of diversity and depth of analysis, and we therefore posit three corollaries (see Table 1). The first corollary follows directly from H1 and the reasoning that deep analysis in less diverse groups leads to the highest creativity because differences in deep knowledge are accessed and effectively applied to produce novel and useful solutions, or:

HYPOTHESIS 2. Less diverse groups that engage in deep analysis will generate and apply the most creative ideas.

While diversity is a resource endowment that is static in nature, depth of analysis is a dynamic concept that can be triggered by the task, incentives, and other factors that usually are independent of group composition. Deep analysis is key for accessing differences in deep knowledge in less diverse groups, as per hypotheses one and two. However, deep analysis also helps diverse groups explore (non-deep) knowledge with potentially creative results. Therefore, we also posit that:

HYPOTHESIS 3. Diverse groups that engage in deep analysis will generate and apply less creative ideas than less diverse groups that engage in deep analysis, but will generate and apply more creative ideas than groups that do not engage in deep analysis.

When comparing groups that engage in non-deep analysis we expect the endowment effect from diversity to dominate over the effect of depth of analysis. The difference is that less diverse groups need to engage in deep analysis to explore their differences in deep knowledge to generate and apply novel ideas in useful ways, while diverse groups have differences in non-deep knowledge that can contribute to creativity even without engaging in deep analysis. Group creativity involves accessing group member differences as well as applying them, and while less diverse groups might be better at application, without deep analysis they will have fewer opportunities to generate novelty.

HYPOTHESIS 4. Diverse groups that engage in non-deep analysis will generate and apply more creative ideas than less diverse groups that engage in non-deep analysis.

In summary, we expect that less diverse groups that engage in deep analysis generate and apply more creative ideas than diverse groups that engage in deep analysis. Moreover, diverse groups that engage in deep analysis will generate and apply more creative ideas than those that engage in non-deep analysis. Finally, in the case of non-deep analysis, we expect that diverse groups to outperform less diverse groups in terms of creativity.

Insert Table 1 about here

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3. Method

3.1. Setting and Sample

135 MBA students at a North-Eastern US university were randomly assigned to groups in a

seven-week MBA class in Human Behavior. Each group selected four out of six unique managerial problems presented in Harvard Business School cases to analyze in writing. We randomly selected a subset of three of these six cases to analyze. The two selection rounds resulted in each group being represented between one and three times in the data. Our final data set consists of 54 case analyses completed by 135 participants on 26 groups. The number of group members varied between four and six, with a mean of 5.15.

The sample has several positive features: the groups were performing a task in a naturalistic setting, allowing us to obtain unobtrusive observational data. The task is to solve a managerial problem, allowing us to test the role of creativity in a managerial setting rather than the more commonly tested product development one. Using a case text allows us to evaluate the analysis of the problem at hand, rather than focusing on idea generation and application.

The groups varied on educational and national diversity, while they were more similar on other diversity dimensions (among the 135 students, 17 were women and 2 were African-Americans; there was also little variance in age (M = 27, S.D. = 3.5 years) and work experience (M = 3.8, S.D. = 2.6 years). Group membership lasted more than two months, which should offer more opportunities to adjust to the group composition and not just offer initial effects of diversity.

3.2. Measures

Knowledge diversity. To measure diversity in member knowledge we use differences in educational background based on group members' undergraduate major. We test two metrics to distinguish between two levels of diversity, one based on academic area and a more fine grained based on degree major, acknowledging that even different majors within an academic area provide meaningful differences.

In the sample there were six academic areas: engineering, business administration, social sciences, humanities, arts and natural sciences; and 32 unique undergraduate majors: of which the most common were economics; electrical, mechanical, and industrial engineering; computer science; and business administration. (In fact, there are ten undergraduate engineering degrees.) We used Blau's (1977) index $(1-\sum p_i^2)$, where p_i is the fraction of group members with area or major *i*. Blau's index treats data as categorical, so there is no need to make any assumptions about differences across academic areas or majors. While the groups in our sample cover the entire range of possible values of the index for academic areas (M=.66, ranging from 0 to .83), the index for majors represent the high end of Blau's index (M= .76, ranging from 0.56 to 0.83, see Table 2).

Creativity

We used textual analysis to generate a measure of creativity. Each case write-up was unitized into *meaningful actions* for an organization or person described in the case, and therefore had to contain at least one verb and could be as long as one sentence. The case write-ups contained from 60 to 229 units, and we selected 10 percent randomly to check for unitizing reliability. Disagreement between the raters was very low (Guetzkow's [1950] $U = .03$).

We coded each unitized segment for the type of statement it contained. Statements could be geared towards (a) the identification and analysis of problems; (2) offering solutions to identified problems; or (3) discussing the expected outcome if a suggested solution is implemented. Since creativity is usually conceptualized as idea generation and application, we identified and isolated the two latter types of statements, i.e., suggestions and expected outcomes, as our measure for creativity. The inter-rater reliability for separating descriptive/analytic statements from suggestions and expected outcomes was high: Cohen's (1960) kappa varied between .77 and .86 across the cases, indicating excellent agreement (Fleiss, 1981).

Suggestions and outcomes were classified into higher-order categories for each case. The cases were of different degrees of complexity and we ended up with 10, 17 and 20 main solution categories for the three cases. Examples of main categories are 'involve higher management' (which include more detailed suggestions as 'involve HR manager', and 'involve the CEO') and 'train employees' (with subcategories like 'organize training for new colleagues' and 'organize regular re-trainings'). Each solution unit can consist of a suggestion, elaborations on the suggestion, and discussions about possible consequences of implementing the suggestion. A solution unit could be as short as a partial sentence or as long as a paragraph with various sentences. Interrater agreement for topic designation was perfect (100% agreement).

As we define a creative idea as a novel and useful idea, we first coded the level of usefulness of a suggested solution. To that end, we distinguish between three aspects of usefulness. First; is the solution <u>actionable</u>? An example of an actionable solution is: 'the company should be a technology leader again and start developing caps for plastic containers as the usage of plastic in the container industry is increasing'. A solution that is non-actionable is: 'the company should change their culture into a winning spirit'.

Second; does the solution include <u>specific</u> instructions? For example, 'the meeting should be postponed' is an actionable solution that is, however, not very specific. Groups that proposed that 'the meeting should be postponed with one week' offer a solution that is more specific, and, therefore, more useful.

Finally, the third aspect of usefulness that we include pertains to whether the solution is <u>valuable</u>, i.e., does it contribute to solving the problem at hand? A group proposed, for example, to 'Do nothing and let the company lose market share even further. Finally things would get so bad that the workers and management will realize that things need to be changed and they will cooperate. Upper management will obviously disapprove of this tactic and you could very quickly fall out of their favor.' This suggestion is actionable and concrete, but, as the group already indicates, it is not the road to a rapid company recovery, nor will it contribute to a manager's personal success.

Inter-rater reliability tests on 11% of the cases resulted in a Coehn's kappa of 0.71, which is deemed a "substantial" agreement by Landis & Koch (1977). .

To compare the groups' novelty, we created a vector for each case with 10, 17 or 20 variables representing the main categories. A variable takes value 1 if the group had suggested that solution and the treatment of the solution was actionable, specific and valuable, otherwise it is set to 0. That is, all three usefulness criteria had to be fulfilled. On average a group report contained 6.2 useful suggestions (the means for the three cases being 4.4; 8.4 and 5.7), ranging from 1 to 14. Each group's vector was then correlated with the vector containing the fraction of all other groups that had suggested that solution. The resulting correlation was standardized for each case to allow for comparisons across cases. Having a high value on the measure means offering a similar set of suggestions as other groups, having a zero value means no relationship to other groups and negative values means covering only what others do not. Since high novelty is associated with creativity and was the outcome we wanted to predict, we reversed the measure (we added 2 to the variable) to allow high positive values to instead mean high rather than low creativity. This reverses the signs on the regression coefficients but does not impact the estimated coefficients or their standard errors, and makes interpretations of the results easier.

Our correlation measure compares a group's combination of solutions to those of all other groups, rather than summing up each solution's novelty, thereby letting the measure take into the account that co-occurrence of ideas might mean that they are less independent from each other, for instance.

As a robustness check we also tested the Goncalo and Staw's (2004) frequency measure, which rates solutions on the frequency with which they occur – more frequent solutions get a higher score, and then adds up a group's scores. For example, if the focal group has mentioned solutions A, B and C; ten other groups also mentioned A; two other groups mentioned B and only one other group mentioned C, the score for the focal group is 13. Since a high score indicates similarity, we reversed the score for ease of interpretation. All results stayed the same using the Goncalo & Staw's (2006) frequency and our correlation measure, but we prefer the correlation measure since it is less sensitive to dependence between solutions.

Depth of Analysis: To understand depth of analysis, we also used textual coding, focusing on how groups used information in their analysis of the problems. To assess depth of analysis, we used the statements categorized as geared towards the identification and analysis of problems (this distinguishes our independent variable - depth of analysis - from our dependent variable – creativity - for which we used the two other types of statements). In the descriptive/analytic statements, information from the case description was repeated, problems identified, and causal links between problems suggested. Each text unit was coded into different topic categories and the depth of analysis measure captures the average amount of information presented within each covered topic (Montoya-Weiss, Massey, & Song, 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. 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).[1]

3.3. Control Variables

We tested a large number of control variables but only include four here, for reasons of statistical power and parsimony. No control variable impacted the dependent and independent variables at the same time; this is why we have no omitted variable problem with ensuing model misspecification (cf. Greene, 2003). Three variables addressed compositional characteristics of the groups other than educational diversity: average GMAT scores of group members, number of native languages of group members and group size. We also used a process control for conflict in the group. See Table 1 for means and standard deviations.

Group conflict. We measured group 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 group, leaving us 64 (64%) usable questionnaires (M = 3 questionnaires/group). For groups 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 groups.

Average GMAT score. The risk of endowment effects due to clustering of higher-ability members is managed by controlling for group averages in GMAT scores. The values ranged between 578 and 646.

Group size. We controlled for group size to rule out the possible alternative explanation that larger groups have the potential to be more diverse, experience more conflict, etc, and that size might be driving any effects.

Native languages. The groups contained members of different nationalities, and to control for any effect of language barriers we included a count of native languages spoken in each group.

4. Results

All three main constructs, the uniqueness measure, diversity and depth of analysis are reasonably orthogonal to one another (see Table 2 for correlations). The interaction term is highly correlated with its two components, as should be expected. Conflict is significantly and negatively correlated with diversity and group size, that is, larger and more diverse groups experience less conflict. Finally, the number of languages in a group and group size are positively correlated.

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[1] Interestingly, the correlation between the depth of analysis and the creativity measure is low and negative: -.24 ($p<.10$) (see Table 2).

Insert Table 2 about here

The research design included groups appearing more than once in the dataset, thus we used a panel-data estimation method to control for repeated observations. To test our hypotheses, we chose a specification that estimates population-averaged effects with robust standard errors. The population-averaged model provides estimates that respond to the question: what happens to a group with characteristics [*a, b,…,n*] when we alter *x* one unit (rather than the random effects model that provides estimates responding to the question: what happens to group *i* with characteristics [*a,b,...,n*] when we alter *x* one unit [Sribney, 1999]). Robust standard errors allow for intragroup correlation and manage misspecification by using bootstrap or jackknife methods[2] (Stata, 2010).

Insert Table 3 about here

Since we are interested in the interactions between diversity and depth of analysis, we must evaluate the joint significance of the main and interaction term coefficients (the separate regression coefficients are without interest by themselves, since their value and standard error depend on each other [cf. Brambor, Clark, & Golder, 2005]). *The diversity* main effect is both significant on its own (p<.01) and is jointly significant with the interaction term *diversityXprocessing*, or:

dDV/d(div)=d(-3.10*div-2.09*div*processing)=-3.10-2.09**processing* is significant on the .01 level (chi(2)= 11.02, p<.004). Similarly, the joint significance of *depth of analysis* and *diversityXprocessing* is significant (chi[2]=10.24, p<0.006)). The effects are graphed in Figure 2a, where the highest and lowest points are connected for low and high *diversity*, and in Figure 2b for low and high *depth of analysis*.

Insert Figures 2a and 2b about here

We hypothesized that homogenous groups that engaged in deep processing would enjoy the highest creativity (H2) and that, in contrast, homogenous groups that did not engage in deep processing would be the least creative (H4). Our predictions for heterogeneous groups were parallel to those for the homogenous groups – deep-processing groups should outperform the non-deep processing groups (H3 and H4).

Computing the joint effects for the three cases (using the min and max values in the data for group diversity and depth of analysis), we find support for hypotheses 1,2 and 4, but the order of hypotheses 3 and 4 is reversed. This means that for groups that did not engage in deep processing,

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[2] The two methods provide the same results.

homogenous groups generated and applied more novel ideas than heterogeneous groups. See computed marginal effects and test statistics in Table 4.

5. Discussion and Conclusion

We set out to do two things in this paper. First, we were interested in studying the application of novel ideas. While creativity is the generation of novel and useful ideas and solutions, most research to date has only studied the generation of the novelty aspects of creativity. Less is known about the useful applications aspect of creativity. Second, we also questioned the well established notion that diversity in groups necessarily leads to creativity by arguing that to the extent that less divers groups can tap differences in deep knowledge, they can prove to be more creative than diverse groups. Indeed, our findings provide support for our argument that when less diverse groups engage in deep analysis, they are more creative (both in terms of novelty and usefulness) than diverse groups. However, in contrast to our expectation, diverse groups who engaged in deep analysis turned out to be less creative than either less diverse groups or diverse groups that engage in non-deep analysis. Our findings suggest re-thinking the role of non-overlapping knowledge in explaining the link between diversity and creativity. Instead, future research might consider the moderating role of depth of analysis when understanding the link between diversity and creativity.

To date, most research has converged on the view that diversity is positively related to creativity. That is, the greater the amount and the greater the variety of different knowledge a group can access, the more creative the group should be. This perspective is based on the view that such exposure provides the opportunity to consider a greater variety of different ideas and the ability to generate novel ideas by building off disconnected ideas – i.e. the more distant two ideas are, the more novel they will be when combined (e.g. Sutton & Hargadon, 1996).

However, that we have shown that it is possible for less diverse groups to generate and apply more novel ideas than diverse groups suggests that the amount and variety of differences is not the only possible path to creativity. In fact, our findings suggest that another way to creativity is the type of differences in knowledge. As we have theorized, even in a completely non-diverse group of engineers, no two engineers have exactly the same knowledge. There must be some differences in knowledge that accrues from unique interests and experiences. Thus, while there is certainly a greater non-overlap between an engineer and a biologist (in terms of both non-deep and deep knowledge differences), engineers have a non-overlap in terms of deep knowledge. When this non-overlap in deep knowledge can be properly accesses and used, we argue that these differences can really drive creativity. Indeed, we suggest that differences in deep knowledge can push thinking alternatively much further than differences in non-deep knowledge. This is because differences in deep knowledge challenge the foundations and assumptions of an idea whereas differences in non-deep knowledge is useful only to the extent that it can help provide an alternative view but not in a fundamentally different way. Moreover, less diverse groups have the requisite expertise and know-how to really dig into the deep-differences and apply these differences to their own ideas to think differently

It is possible, of course, that a biologist can influence an engineer to think fundamentally different. This happens when an engineer can access and use the differences in deep knowledge from a biologist to really think differently in paradigmatically different ways. Indeed, researchers have found that combining different knowledge to generate new and useful alternative perspectives depends on analogical reasoning (Gentner & Markman, 1997; Holyoak & Thagard, 1995). Analogical reasoning is the process of identifying a specific case/example from one's previous experience and looking for similarities between this case and the new case/problem at hand. By identifying the similarities between the old and new cases, one can use or adapt the solution from the old case to develop a new solution to the new case. Thus, to the extent that diverse groups are able to engage in analogical reasoning, creativity will flourish. However, it is worth noting that the research on analogical reasoning and creativity have also found that deep analogical reasoning leads to greater creativity than surface analogical reasoning (Blanchette & Dunbar, 2000); where the difference between deep and surface analogical reasoning refers to the former being similarities in deep structural ways and the latter refers to surface similarities only. Given that less diverse groups are better positioned to use and apply differences in deep knowledge, less diverse groups are likely to engage in analogical reasoning that is deeper than the analogical reasoning that diverse groups will engage in. Thus, less diverse groups should be better positioned to be more creative.

An important condition for our finding that less diverse groups are more creative than diverse groups is the engagement in deep analysis. This is consistent with recent calls to shift the focus from studying diversity per se to a closer focus on the moderating mechanisms that explain creativity (Hülsheger et al., 2009; Mannix & Neale, 2005). In identifying depth of analysis as a moderator, our findings make a contribution by showing that the depth of analysis determines the kind of differences in knowledge that is accessed and used within a group to generate and apply new ideas and solutions. Whereas depth of analysis draws out differences in deep knowledge, non-deep analysis draws out differences in non-deep knowledge. Thus, to the extent that a moderator can draw out differences in deep knowledge is better for creativity than drawing out only differences in non-deep knowledge.

Moreover, creativity is not merely the generation of novelty but the generation of novelty that is applied in useful ways to develop a good solution (Taylor & Greve, 2006). In fact, given our finding that deep analysis facilitated creativity in less diverse groups was accompanied by an unexpected finding that deep analysis resulted in the worst creativity in diverse groups further suggests that the effective application of novel ideas is just as important, if not more important, than generating novelty. That is, the reason why less diverse groups engaged in deep analysis are most creative is because they can draw from differences in deep knowledge and also have the ability to effectively apply the novel ideas that emerged from deep analysis. In contrast, diverse groups engaged in deep analysis are least creative because even though deep analysis draws out differences in deep knowledge, diverse groups are unable to effectively apply the ideas borne of these differences in deep knowledge.

We conclude with the key managerial implication that managers should depart from the traditional view of how diversity in groups is linked to creativity. This is not to say that diversity is bad for creativity. Rather, our findings show that under the right conditions, both diverse and less diverse groups can be creative. Instead, to the extent that a manager has control on the group they assemble, managers need to recognize when putting together a less diverse group is more conducive to the task at hand (e.g. solving a finance problem in the company) and when putting together a diverse group is more conducive (e.g. designing new consumer products). Finally, when managing a less diverse group, a manager will do well to remember to emphasize deep analysis whereas when managing a diverse group, the manager should avoid deep analysis.

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Table 1 Interactions and their hypothesized relative impact on creativity, 1>2>3>4 in contribution to group creativity; and (in parenthesis) actual impact on creativity

		Depth of analysis	
		Low	High
Diversity	High	3	2 (4)
	Low	4 (2)	1

Table 2 Descriptive statistics and correlation table.

	Variable	Mean	St. Dev.	Min	Max	1	2	3	4	5	6	7
1	Creativity	1.99	0.99	0.24	4.06							
2	Diversity	0.76	0.08	0.56	0.83	-.15						
3	Depth of processing	0.00	1.00	-1.84	2.97	-.24+	-.16					
4	Div*DoP	-0.01	0.74	-1.44	1.90	-.25+	-.16	.99**				
5	Conflict	3.09	0.78	1.4	4.2	-.19	-.10	.03	.02			
6	Avg GMAT	614.27	17.74	578	646	-.18	-.16	.02	.01	.07		
7	Group size	5.13	0.55	4	6	.06	.01	-.09	-.10	-.28*	.22	
8	Languages	2.90	1.09	1	5	.24+	-.01	-.06	-.05	-.53**	-.21	.27*

** p<0.01, * p<0.05, + p<0.1

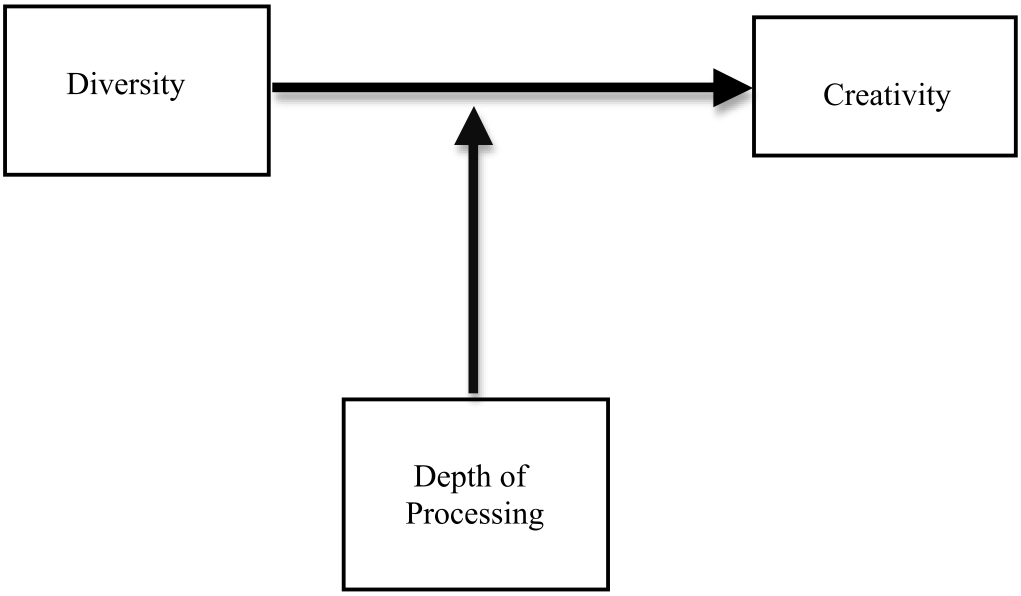
Table 3 Results of population-averaged panel-data estimations with robust standard errors.

	(1) rallS	(2) rallS	(3) rallS	(4) rallS	(5) rallS	(6) rallS	(7) rallS
DeepDiversity		-3.07**		-3.08**	-3.10**		-3.17**
		(1.15)		(1.16)	(1.11)		(1.14)
Depth of Analysis		-.28**	-.22*	-.28**	1.28+	-.14	1.40+
		(.10)	(.11)	(.10)	(.69)	(.41)	(.77)
DepDivXDoA					-2.09*		-2.08*
					(.98)		(.96)
Conflict	-.19	-.29*	-.20	-.29*	-.30*	-.20	-.31*
	(.16)	(.13)	(.15)	(.13)	(.12)	(.15)	(.12)
Avg gmat	-.01	-.01*	-.01	-.013*	-.014*	-.01	-.01*
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Size	-.08	-.15	-.13	-.15	-.17	-.12	-.16
	(.20)	(.18)	(.21)	(.18)	(.16)	(.22)	(.17)
Languages	.16	.09	.12	.09	.09	.12	.09
	(.13)	(.10)	(.12)	(.10)	(.10)	(.12)	(.10)
SurfaceDiversity			-.23	.02		-.18	.22
			(.30)	(.32)		(.47)	(.43)
SurfDivXDoA						-.14	-.25
						(.75)	(.70)
Constant	8.35*	13.60**	9.20*	13.57**	14.59**	9.25*	14.55**
	(4.06)	(3.61)	(4.02)	(3.64)	(3.71)	(4.06)	(3.70)
Wald Chi2 (dof)	9.07+	35.80**	16.80*	37.01**	46.16**	17.53*	59.84**
Observations	55	54	54	54	54	54	54
Number of group	26	26	26	26	26	26	26

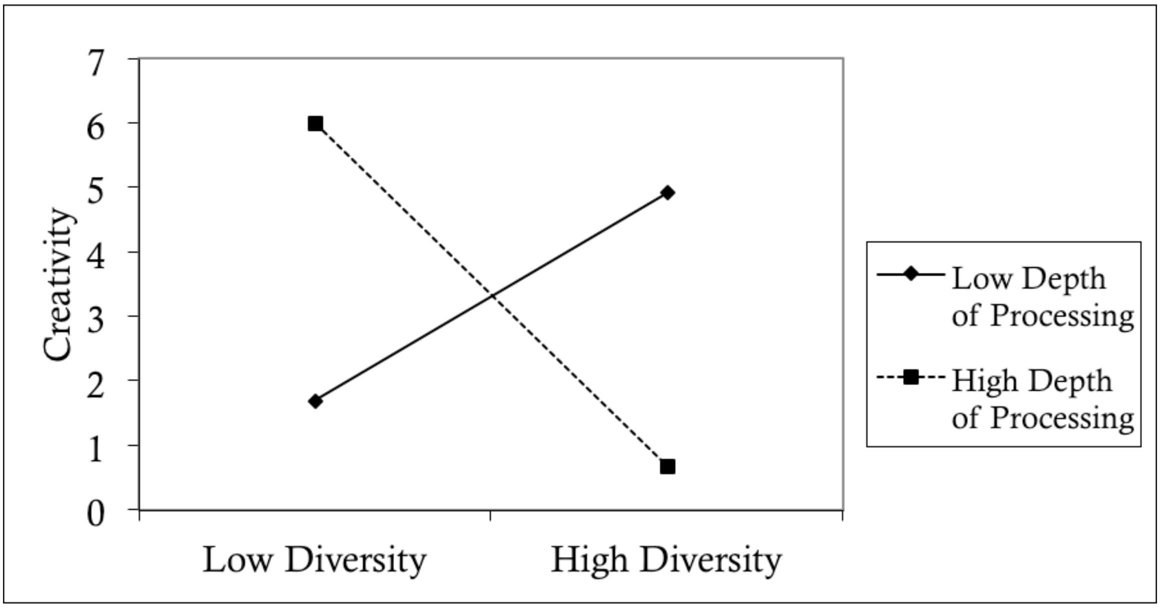
Standard errors in parentheses
** $p<0.01$, * $p<0.05$, + $p<0.1$

Interaction tests: All DeepDiversity interactions significant at $p<.05$ level. No SurfaceDiversity interactions significant.

Figure 1 Hypothesized model.



Figures 2a **The effect on creativity of less deep versus deep processing changing with level of diversity.**



Figures 2b **The effect on creativity of homogenous versus heterogeneous groups as they pursue different depth of analysis.**