

Explaining idea sharing mechanisms: Linking diversity and network factors
to explore creative teams

Sophia Sullivan, Casey Pierce, Paul Leonardi & Noshir Contractor
Northwestern University

Academy of Management Annual Conference, Lake Buena Vista, FL, Aug. 9 – 13.

Correspondence: sophiasull@gmail.com

ABSTRACT

Innovation is largely a product of teams. By sharing ideas with other team members, teams can leverage good ideas for innovative outputs to a greater degree than creating alone. However, team processes can ignite or stymie the creative process by influencing idea sharing among team members. Thus, we propose investigating how sociopolitical team dynamics shape the likelihood of team members contributing new ideas and supporting the ideas of others. We develop an agent-based model to simulate how both team demographics and network attributes influence creative outcomes of teams. Our simulations suggest demographics and network attributes play a role at different stages of the idea sharing process.

Explaining idea sharing mechanisms: Linking diversity and network factors
to explore creative teams

INTRODUCTION

Rather than relying on the sole creative genius to develop an innovative breakthrough, organizations increasingly depend on teams to leverage a mix of diverse skillsets, backgrounds and perspectives to help generate creative ideas (Hargadon & Sutton, 1997; Paulus & Yang, 2000; Sutton & Hargadon, 1996). As ideas are shared, team members accept, reject and recombine various ideas, developing new innovations (Carlile, 2004; Paulus & Yang, 2000; Phelps, Heidl, & Wadhwa, 2012). When the creative assets of team members are effectively pooled together, the team's creative potential is greater than the sum of its individual creative parts. Thus, the members comprising the team and their interactions among one another are influential factors in the collective creative outcome (Martins & Shalley, 2011).

Nevertheless, teams can be problematic. While creative teams can ignite innovation through the process of idea recombination; team processes can stymie creative potential in teams (Diehl & Stroebe, 1987, 1991). As social behavior literature suggests, individuals in teams are largely influenced by their relationships which are reinforced by shared similarities (Tajfel & Turner, 1979; Tajfel, 1974). In terms of creativity, social influences can bias team members' objective evaluation of their peers' ideas.

One of the reasons why social influence is important for managing creative teams is because it can affect the idea sharing process. Social ties influence how ideas are shared within teams such that individuals who are connected to others feel socially supported and are more likely to share their ideas (Mannix & Neale, 2005). Furthermore, teams also require a range of ideas in order to have opportunities for recombinant creativity (Fleming, 2001; Murray &

O'Mahony, 2007). Thus, while access to new ideas is instrumental in the innovation process, ineffective idea sharing reduces the likelihood of considering all potential creative options, which in turn shrinks the pool of potentially creative ideas to recombine.

While the literature is rich with research describing how to design creative teams (Ancona & Caldwell, 1992; Reagans, Zuckerman, & McEvily, 2004), scholars are divided as to how various factors influence creativity in teams. One camp posits that the team's demographic composition (e.g., gender, race, tenure, etc.) predict creative team performance (Martins & Shalley, 2011; Williams & O'Reilly, 1998). On the other hand, a second school of thought focuses on the network position of the individual, suggesting individuals who occupy high-valued brokerage positions have better access to diverse ideas, thus offer a greater value to the team's creative potential (Balkundi, Kilduff, Barsness, & Michael, 2007; Burt, 2004; Fleming, 2001). The literature that considers both of these standpoints seeks to prove the merits of one over the other (e.g., Amabile, Conti, Coon, Lazenby, & Herron, 1996; Greg R Oldham & Cummings, 1996; Reagans et al., 2004; Uzzi & Spiro, 2005; Amabile & Barsade, 2005), rather than reconciling how both perspectives can better inform the design of creative teams and predict their creative outcomes. In this paper, we propose that both camps have complementary findings. Thus, we seek to combine both streams of literature by developing a simulation model to test how demographics and network structure both influence the creative process through the communicative mechanism of idea sharing.

Findings on the effects of team diversity from both demography and network scholars leads us to question how we should form creative teams. Moreover, once creative teams are formed, what is the value of the creative outcomes they produce? Since much of the team creativity research focuses on the quantity of ideas, we propose measuring not just the number of

ideas teams generate, but also the value of creative outcomes. However, given methodology constraints, there are limitations to how teams can be manipulated (Reagans et al., 2004), which is why we adopt using simulation models so we can manipulate the team's profile in order to test a range of team configurations.

THEORETICAL FRAMEWORK

Idea Sharing in Teams

Although the literature suggests a myriad of definitions for creativity¹ (Amabile, 1996), a theme consistent across classic theories suggests individual creativity is better supported through social interactions (Simonton, 1984; Allen, 1977; Kanter 1988). Woodman, Sawyer and Griffin (1993) propose the *interactionist framework* to describe the interplay between individual creativity and the social context. Building upon the interactionist framework, more recent scholarship continues to shift the focus from the individual creator to social creativity as a collaborative process (Martins & Shalley, 2011; Perry-Smith & Shalley, 2003; Perry-Smith, 2006; Sutton & Hargadon, 1996).

The collaborative process allows for recombination of ideas, which is considered by many to be the primary source of novelty (Henderson & Clark, 1990; Murray & O'Mahony, 2007). As Fleming and Mingo (2008) summarize, recombination is an inherently social process,

New combinations do not arise in the 'ether' between individuals. Social influences are obviously strong; creative combinations arise within an individual, are expressed (though not necessarily understood correctly), and inspire colleagues in their further recombinant search. (Fleming & Mingo, 2008) (p.115)

¹ We assume a definition of creativity in which actors develop ideas that are both novel and useful. We explicitly distinguish creativity from innovation, which involves the implementation of those ideas into products and processes.

Creative recombination requires team members to contribute their existing ideas in order to create novel ideas (Burt, 2004; Fleming, Mingo, & Chen, 2007; Fleming, 2001). Thus, the perspective that teams are instrumental for recombination draws attention to the strength of collective creative power (Hargadon & Bechky, 2006). Specifically, collaborative creativity allows opportunities for novel recombination of ideas through the social interactions among a diverse group of people (Fleming et al., 2007; Uzzi & Spiro, 2005). Through social interactions, teams can develop creative ideas that are more than the sum of its individual parts.

Nonetheless, creativity begins within the minds of individuals when an idea is first conceived. However, creativity “is not the product of single individuals, but of social systems making judgments about individuals’ products” (Csikszentmihalyi, 1999: 14). Although the concept of recombination is well agreed upon as the source of novelty, there is little understanding on the mechanisms by which recombination occurs. In this paper, we propose that idea sharing is the beginning stage in which collaborative recombination occurs within teams.

Literature on brainstorming in teams does suggest that idea sharing is the communicative mechanism by which team members discover new ideas and recombine those ideas for creativity (Baer, Oldham, Jacobsohn, & Hollingshead, 2008; Lazer & Friedman, 2007; Sutton & Hargadon, 1996). When individuals share their ideas, the team is able to produce creative ideas that surpass the creativity from of one individual (Kurtzberg & Amabile, 2001). The process of idea sharing also allows for individuals to discover new ideas they had not considered before, to offer ideas of their own, and to improve upon the ideas of others (T. Amabile, 1996). However, ideas cannot spontaneously rearrange themselves without first being shared among team members. Consequently, recombination can only occur when ideas are expressed regardless of whether they exist in the minds of team members (Kurtzberg & Amabile, 2001).

Diversity and Social Processes in Creative Teams

People enter teams not just with their ideas, but also their influence and social relationships, thus team creativity is socially dynamic in nature. The processes of idea sharing and recombination are embedded within a sociopolitical context. Under ideal circumstances, all individuals would equally share ideas and their contributions would be evaluated for their inherent creative quality. However, ideas are inextricably linked to their creators. Thus, idea sharing does not occur within a vacuum, but is instead predisposed to each team's unique sociopolitical context. The diversity of a team influences these social processes and shapes the creative output.

Diversity increases exposure to a more expansive set of ideas, as each individual has a different thought world and frame of reference (Dougherty, 1992; Carlile, 2002). The process of connecting ideas from different thought worlds challenges old paradigms, which results in creativity. In turn, diverse teams have access to potential new ways of seeing creative solutions by combining individuals' different perspectives. For example, (Hargadon & Sutton, 1997; Sutton & Hargadon, 1996) describe how a successful design firm employs individuals from diverse disciplines during their brainstorming sessions to encourage different perspectives to the problem at hand. The eclectic design team is able to collaborate creatively by challenging previously held design assumptions to recombine ideas from their different functional domains. As Hargadon and Sutton's findings show, leveraging diversity is one way to encourage new ideas and reconfiguration of those ideas.

Scholars adopting the stance that demographic diversity is important for team creativity argue that heterogeneous teams have increased interaction with new ideas (McLeod, Lobel & Cox, 1996; Jackson, 1992; Cox and Blake, 1991; Cox, 1991). Although increased demographic

diversity has benefits for creativity, it is not necessarily conducive for effective idea exchange. Heterogeneous teams are more likely to be inflicted with conflict (Harrison & Klein, 2007; Tajfel & Turner, 1979; Williams & O'Reilly, 1998), thus hampering the idea sharing process. While some studies indicate such conflict can be beneficial for teams because it incites team members plagued with groupthink to critically consider better idea alternatives (Callaway & Esser, 1984; Janis, 1972), other findings suggest conflict adversely affects communication performance in teams (Chen, 2006), undermining the open idea sharing process. Moreover, the increased heterogeneity in teams reduces team cohesion (Williams & O'Reilly, 1998), which in turn decreases trust among members (Coleman, 1988). Having some degree of mutual trust is often necessary for creative teams, particularly when individuals may perceive a level of risk in sharing ideas that diverge from the mainstream way of approaching problems (Mannix & Neale, 2005). Thus, we present two propositions regarding team diversity and idea sharing:

Proposition 1a: Demographic diversity will stymie the idea sharing process such that team members will share less and have a tendency to reject more ideas.

Proposition 1b: Since demographic diversity weakens the idea sharing process, demographic diversity will decrease the creative value of recombined ideas.

Network Structure and Creativity

The perspectives of scholars adopting a network structural approach actually complement those of demography researchers with regards to team diversity. For instance, Reagans, Zuckerman & McEvily (2004) propose that demographic diversity has conflicting effects on team performance by increasing the availability of new ideas to the team but also weakening the strength of relationships among team members. Fleming, Mingo and Chen's (2007a) research on patent data found that inventors who had similar ties, represented by teams with higher cohesion,

had a higher likelihood of being able to spread their ideas within the team. However, their findings also suggest that lower cohesion enabled inventors to better access new ideas. Taken together, their findings indicate that balanced networks are advantageous for identifying potential breakthroughs, but such creative ideas are best nurtured within a cohesive team network to gain traction and subsequent opportunities for recombination (Fleming et al., 2007).

Although brokers are advantageously positioned to receive diverse ideas, they may not present their ideas or they may not garner enough support to have their ideas accepted. As previously discussed, creative ideas remain stagnant until individuals decide to share those ideas with their team, and social support within a team can help encourage team members to share their ideas. From a network perspective, people perceive they have social support from those in which they have already formed relational ties. Strong ties moderate feelings of trust and comfort (Granovetter, 1973) – relationships which would boost morale for individuals to share their creativity. Thus, we present two propositions regarding the influence of team networks on creative outcomes:

Proposition 2a: There is a curvilinear effect of network balance on the idea sharing process. Networks should have a moderate level of balance to optimize idea sharing and support of ideas within the team.

Proposition 2b: Of the ideas that are accepted, moderately balanced networks will have ideas with the highest creative value.

In summary, Figure 1 below illustrates the aforementioned propositions and which describe how individual demographic characteristics influence both the team network and team process. Specific individual demographics, such as gender, race and tenure are expected to influence the team network - specifically, in how the network is configured through the principle

of homophily. In other words, individuals who share similar gender, race, tenure and functional backgrounds are more likely to form ties with one another. Team diversity literature shows support for this.

INSERT FIGURE 1 ABOUT HERE

METHODOLOGY

The focus of this work is to explore the mechanisms by which a creative output is produced. Although much research has been conducted that explores the effect of demographics (Ancona & Caldwell, 1992; Cohen & Bailey, 1997), network position (Aral & Van Alstyne, 2011; Burt, Jannotta, & Mahoney, 1998; Gargiulo & Benassi, 2000) and internal team process (Ancona & Caldwell, 1992; Balkundi et al., 2007; Cohen & Bailey, 1997; Drazin, Glynn, & Kazanjian, 1999) on team output, very little has been done that considers multiple approaches (see (Balkundi et al., 2007)), and even less has been done that incorporates all of these theories. It would be nearly impossible to test all these theories and their mechanisms simultaneously in the field, so we propose simulation as an alternative methodology to the traditional sociometric methods (i.e. ethnographies and surveys).

Simulation in general, and more specifically, agent-based simulation, has gained traction in recent years as a new approach to studying human behavior in organizations and in teams, following a call to action by Macy & Willer (2002). Any type of simulation does have limitations. Validation is extremely difficult with simulations and requires extensive data, which is often unavailable. Even with a high degree of validation, the results from a simulation cannot prove or disprove a theory; however, simulations do provide many advantages. In an area such as team creativity and performance, the plethora of research in the area provides a solid foundation of documentation upon which to build the assumptions of the model. In addition, the

construction of simulations requires significantly less time and resources than the traditional sociometric methodologies.

Model Mechanisms

Homophily and cognitive shortcuts. Newly formed teams with strangers have a predisposition for taking cognitive short cuts. These teams are often used for creative development, and managers purposely assemble people from different functional areas or departments. Often times these teams are temporary and last for the duration of new idea development. The demographic composition is particularly influential for newly formed teams. Visible demographic characteristics such as gender, race and ethnicity are particularly salient. Such demographic characteristics have a particularly strong influence upon newcomers to form ties with similar others (Harrison & Klein, 2007; Mollica & DeWitt, 2000). Even with non-visible attributes such as tenure, individuals have the tendency to bond and form close relationships with their organizational cohorts, developing a shared identity from experiencing the organization from a similar entry to the organization (Ancona & Caldwell, 1992). Thus, the degree of demographic diversity not only drives the range of perspectives within a team which would shape the creative ideas, but diversity also affects the amount of open communication and how social ties are created and reinforced. We therefore propose the following mechanism:

Mechanism 1: Demographic non task-related diversity affects team cohesion through the formation of homophilous network ties.

Idea-related demographics. While demography literature focuses on individual characteristics and how they manifest within a team environment, network scholarship expands the perspective beyond just the individual attributes and also considers the creative capital individuals bring from their interpersonal networks (Burt, 2004; Monge & Contractor, 2003).

Individuals have membership to multiple networks and when individuals participate in creative teams, they still maintain ties to other networks. Thus, as Fleming, Mingo and Chen's (2007) research suggests, exogenous networks become sources of new ideas for the creative team. Brokers, individuals who connect multiple networks, are in a prime position to gain access to new, creative ideas (Burt, 2004). With regards to recombinant creativity, brokers also have an opportunity to recombine ideas across domains that would otherwise remain disconnected (Burt, 2004; Fleming et al., 2007; Lingo & O'Mahony, 2010; Uzzi & Spiro, 2005). Thus, network constraint is an important characteristic that influences a person's creativity.

Several other factors influence the creativity of an individual as well. Some individuals are inherently more creative than others, and this affects the quality of their ideas (Gough, 1979). Gough's Creative Personality Scale (CPS) has been found to predict the an individual's creative potential (Gough, 1979; Oldham & Cummings, 1996). Fleming et al., (2007) also find that expertise is crucial in developing creative ideas, because familiarity with the field is crucial to being able to understand what ideas will be both the most novel but also the most useful (Vincent, Decker, & Mumford, 2002). Therefore, we propose the following mechanism:

Mechanism 2: Demographic task-related diversity affects the team's creative output through the value and variety of ideas generated by team members.

Balance theory. Balance theory states that individuals are uncomfortable with an "imbalance" in their network. In other words, individuals are more likely to be friends with two people are friends themselves.

Moreover, balance theory also informs how team structure can influence idea sharing in teams. Networks that are balanced (Monge & Contractor, 2003) have actors who all share ties within the network. Thus, we would expect a team exhibiting a balanced network to indicate

open idea sharing among team members. On the other hand, if there are a few individuals with some attributes in common and others with none, this will lead to an imbalance in the team that results in lower cohesion:

Mechanism 3: Team cohesion affects the sharing of ideas by its members through balance theory.

Network idea evaluation. In our model, we propose support of an idea is entirely determined by the network. We do this for several reasons. First of all, research does show that even when highly creative people are on a team, their ideas aren't necessarily accepted, and are frequently rejected in uncertain environments (Mueller, Melwani, & Goncalo, 2012), which means that the creativity value of an idea is not the deciding factor in its acceptance or rejection. We assume that social factors are the reason for this, so we emphasize these. The second reason is that we do not want to make any assumptions on individuals being able to recognize the creativity value of an idea, which requires research into cognition and perceptions of ideas. This is a somewhat pessimistic view of creativity, but we take the conservative approach to be able to give stronger results. Groupthink is also a common problem in these teams. Even if an individual has made a positive decision, he may change based on what the other members think (Janis, 1972).

Mechanism 4: The acceptance or rejection of shared ideas during the recombination process is based entirely on the network links between members. Actual creativity value of the idea is not a factor.

Agent-Based Modeling

Agent-based models (ABMs) are perfect for this research for several reasons. First, regardless of organizational environment or other exogenous factors, the output of the team is

developed by the team members, who are agents with their own free will and perspectives. ABMs allow the development of agents that follow behavioral rules and act according to their individual characteristics (Macy & Willer, 2002). Since each agent follows their own rules with randomness, the interactions of these behaviors usually leads to completely unexpected results in the system as a whole. Another strength of ABMs is that they allow a large degree of randomness, since human behavior can never be predicted completely. This is a feature that makes ABMs much more desirable than systems dynamics models, which are completely deterministic (for more information, see (Richardson, 2001)). Indeed, researchers have already been using ABMs to explore teams and organizations (Harrison, Zhiang, Carroll, & Carley, 2007; Lazer & Friedman, 2007a).

This model was developed using NetLogo (Wilensky, 1999), which is an agent-based modeling software. Each model typically contains initialization procedures. Once the setup is complete, the model runs for a specified number of time units, called ‘ticks,’ during which each agent may act or not, contingent on the rules of the model.

In this particular model, initialization includes the assignment of different attributes to the agents, and assembly of the intra-group network. During each simulation, each agent will decide whether or not to share an idea, and decide whether they support the ideas shared by others. The outcome of this model is a creative product, represented by its diversity of functions, the number of ideas that are recombined, and the creativity of the ideas shared.

Model Implementation

Initialization. The first variable is team size, $|T|$, which is allowed to vary from 2 – 10 members for each team T . In accordance with the most common findings of demographic influence, we choose gender, race, tenure and function to effect the construction of the group

network. Users can specify the number of each gender, races represented, functional backgrounds, and range of tenures (0 – 30 years) of the team members. These settings are then used to assign these demographic qualities to each member.

We also use demographic variables to determine the creativity of an individual. Some individuals are inherently more creative than others, and each member is assigned a network constraint, expertise, and Creative Personality Scale (CPS) score. Users can specify ranges on the network constraints (0 – 100%), expertise (0 – 30 years), and CPS scores (0 – 30 units) of members, which are used to assign these traits randomly, according to a Uniform Distribution. A summary of all the variables and distributions is given in Table 1.

Team network tie formation. Once individuals have been assigned a gender (gen), race (rac), tenure (ten) and function (fun), they ‘look’ around the team for similar others, and form links, which are weighted by the number of shared demographic attributes. The total link weight between two members w_{ij} is then the sum of the weights on the link from each aspect of homophily. For example, the contribution of a gender link between two members is:

$$w_{ij}^{gen} = 0.25 * I_{\{gen_i=gen_j\}},$$

where $I_{\{gen_i=gen_j\}}$ is an indicator function with a value of one if the genders of the two members are the same, and zero otherwise. The weights of race and function are calculated in a similar manner.

Gender, race, and function are categorical variables and are thus easy to match; however, tenure is continuous, which means the concept of “same” is more difficult to quantify. Instead, we develop a measure of similarity that depends not only on the tenures of the two individuals under consideration, but also on the tenures of the other team members. For example, given a team with $|T| = 5$, the tenures of members may be: $ten = [1,3,5,7,9]$. In this case, the members

with tenures 1 and 9 will not be similar because the member with a tenure of 3 is more similar to the member with tenure 1, and the member with tenure 7 is more similar to the member with tenure 9. On the other hand, if the tenures of the team are: $ten = [1,9,25,27,30]$, now the members with tenures 1 and 9 are much more relatively similar to each other relative to the other team members with tenures of 25 and above. Essentially, the tenures of two members are similar only as much as they are dissimilar to others. In order to quantify this phenomenon, we developed the following algorithm. First, each agent calculates on average how dissimilar his tenure is to everyone else's, or the Average Tenure Distance, ATD :

$$ATD_i = \frac{\sum_{i \in T} |ten_i - ten_j|}{|T| - 1}$$

Then, if the differences in tenures between two agents are less than both of their averages, they will form a tenure similarity link with each other.

$$w_{ij}^{ten} = 0.25 * \mathbf{I}_{\{|ten_i - ten_j| < [ATD_i]\}} * \mathbf{I}_{\{|ten_i - ten_j| < [ATD_j]\}}$$

The total weight of the link between two agents is then:

$$w_{ij} = w_{ij}^{gen} + w_{ij}^{ten} + w_{ij}^{rac} + w_{ij}^{fun}.$$

Individual idea generation. First of all, each person has an individual CPS score, cps .

Each person also has a network constraint, nc , which represents their position in a structural hole or not. The final variable that influences an individual's expertise, exp . The creativity value of the idea is the average of each of these factors:

$$Idea = \frac{(cps + exp) * \frac{100}{30} + (100 - nc)}{3}$$

The resulting *Idea* value is scaled to be from 0 – 100.

Individual idea sharing. Each agent decides whether to share his or her idea based on his comfort level within the team. In order to quantify the idea of balance and comfort within the team network, we use centralization (Wasserman & Faust, 1994), which is proposed by (Harrison & Klein, 2007) to be a good measure of the disparity of network position among team members. The comfort level of each agent is determined by the agent's weighted degree centrality, wdc , and is relative to the comfort of others in the group. Therefore, centralization captures the degree to which agents are more comfortable than others. We choose weighted degree centrality to represent the overall value of a team member's links to all the other members of the group, which lets us compare how well connected each member is relative to the other members. The individual with the highest weighted centrality is the most comfortable in the group and will always choose to share his idea. The person with the lowest weighted degree centrality is least comfortable and will never decide to share. Every other member has a probability to share, $Pshare_i$, based on the Uniform distribution as follows:

$$Pshare_i = \frac{wdc_i - \min_{k \in T}(wdc_k)}{\max_{j \in T}(wdc_j) - \min_{k \in T}(wdc_k)}$$

Once the agent's probability to share has been calculated, he will make the decision whether or not to share his idea.

Initial idea acceptance. Each shared idea is discussed before discussing the next idea. After a team member shares his idea, the other agents decide in a random order whether they support it ($supp = 1$) or not ($supp = -1$). First, the influence of the link partners, wlp_i , is calculated:

$$wlp_j = \sum_{i \in T, i \neq j, s} supp_i * w_{ij}$$

If a link partner has not yet calculated his acceptance, then $supp_i = 0$ and he does not influence j 's decision. Similarly, if $w_{ij} = 0$, members i and j are not linked and do not influence each other. This measure captures the fact that the amount of influence of link partners depends on the strength of the link. The influence of link partners can be positive or negative (or zero), and the sign is important when calculating the probability to accept. If j has no information from his link partners, he will rely only on the strength of his link with the idea sharer. If the member making a decision does not have any information from his link partners and no link with the person sharing his idea, then he decides randomly whether to support the idea or not. The probability of an individual accepting the shared idea is then:

$$P_{accept_j} = \begin{cases} w_{sj} + wlp_j * (1 - w_{sj}) & wlp_j > 0 \\ w_{sj} * (1 + wlp_j) & wlp_j < 0 \\ w_{sj} & wlp_j = 0 \cap w_{sj} \neq 0 \\ 0.5 & wlp_j = 0 \cap w_{sj} = 0 \end{cases}$$

Individual idea acceptance re-evaluation. We recognize that individuals do change their mind in groups based on the attitudes of others. Frequently, after an individual has made up their mind but the rest of the group does not feel the same way or if a particularly influential person disagrees, they will change their mind (Callaway & Esser, 1984; Janis, 1972). Therefore, members are allowed to change their minds once a decision has been made. There are several conditions that must be met in order for them to reconsider their decision.

First, if an individual's probability to accept the decision, P_{accept_j} , does not change from one time period to the next, then the decision is not re-evaluated². The purpose of this is to ensure that randomness does not cause support to oscillate wildly between acceptance and rejection.

² Here "re-evaluate" means that a P_{accept_j} -weighted coin is flipped to determine whether the idea is accepted or not.

Secondly, the “new information” a member receives must be contrary to his original decision in order to re-evaluate. If a person already decided to accept the idea and P_{accept_j} increases, this probability only reinforces j 's original decision, so j does not re-evaluate. Likewise, if member j has decided to reject the idea, and P_{accept_j} decreases, j still does not re-evaluate. If, however, j has rejected and P_{accept_j} increases, j 's decision is re-evaluated, and vice-versa. The re-evaluation process continues for 5 time units.

Team idea acceptance. Once each member has decided whether to accept the decision or not, the number of supporting members is counted, including the member who originally had the idea. If there is a clear majority for or against (which will be the case in odd-sized groups), then the decision to accept or reject the idea is simple. If, however, there is a tie between number of people for and against the idea, the total weighted degree centrality of each group is used to see which side is more influential. If these numbers are equal, then the decision is counted as a rejection because as is the case with many of these situations, the result of no decision may appear to be the same as indecision. The idea acceptance process is repeated for each new idea shared.

Team idea recombination. Once all the ideas have been shared and accepted or rejected, they are recombined to form a new idea. Even though recombination has been studied by many and is generally considered to be the main source of ideas (Henderson & Clark, 1990; Murray & O'Mahony, 2007), very little research has actually focused on the recombination process.

To create the recombined output of the team, we average the creativity scores for each of the ideas accepted. The number of functions represented by the recombined ideas is also counted as part of the creativity of the idea – a recombined idea that comes from multiple people from only one function will be less creative than a new idea from multiple functional backgrounds.

Finally, to assess the creativity of the recombined idea, we also count the number of ideas represented in the idea.

RESULTS AND ANALYSIS

We calculated several diversity and network metrics in our analysis, which are outlined in Table 1. In order to maintain a parsimonious model, we held constant team size to 4 and only manipulated the model parameters to the settings outlined in Table 1.

INSERT TABLE 1 ABOUT HERE

For our specific set of parameters, our simulation model produced a total of 9,600 runs. We let the categorical variables such as gender and number of races to vary to the full extent, but put no restrictions or assumptions on the expertise, tenure or CPS scores of members, so they were allowed to vary across the entire range. Each model run included several team measures to track the idea sharing process and collective creative outcome. To begin with, for the idea sharing process each model run includes measures for the number of ideas shared and the number of these that rejected. For the outcome measures of the creative team output, each model run also includes the number of accepted ideas, the number of functions represented in the final ideas and the calculated idea score. The latter two measures represent the creative value of the team's ideas. Finally, we computed an aggregate outcome measure multiplying the number of accepted ideas, idea score and the number of functions to capture the overall creative potential of team creativity.

Next, we performed a set of regressions to analyze how demographic variables (gender, race, tenure, function) and network factors (centralization) influence the idea sharing process and creative outcomes of teams. As previously discussed, we built into the model that the presence of highly creative and expert team members who are in structural holes increase the likelihood of

a creative output, thus each regression model controls for the average team CPS, expertise, and network constraint. In total, we present seven regression analyses as detailed in Tables 2 through 7. Collectively, the regression results address our theoretical framework (Figure 1) exploring the influences of demographic and network factors on both the idea sharing process and creative outcomes.

Findings

We present our findings as they relate to our propositions. Our first set of propositions (*P1a, P2a*) focus on how demography and networks respectively influence the idea sharing process. OLS regression results in Tables 2 and 3 summarize the initial stage of the idea sharing process³.

INSERT TABLE 2 ABOUT HERE

The full models in the regression results indicate mixed support for *P1a* and *P2a*. Tables 2 and 3 show the influences on idea sharing prior to the idea acceptance stage. As expected, increased racial and functional diversity decreases the number of ideas shared as shown in Table 2. Instead, increased racial and functional diversity increases the number of rejected ideas as indicated in Table 3. Although gender diversity is showed to positively increase the number of ideas shared at the $p < 0.05$ level in Table 2, the gender diversity coefficient is substantially larger and more highly significant at the $p < 0.001$ level in Table 3. This finding suggests that gender diversity increases the number of rejected ideas more so than increasing the number of accepted ideas. Taken together, these results bolster the finding that diversity can stymie the sharing

³ Before beginning regression analyses, we found evidence of heteroskedasticity in our models even after transforming our variables. Thus, we report robust standard errors as more conservative estimates across all regression models.

process. However, we find that tenure diversity increases the number of shared ideas at the $p < 0.001$ level and has no statistically significant relationship with the number of rejected ideas.

INSERT TABLE 3 ABOUT HERE

As shown in Table 2, the positive linear centralization term and negative squared centralization term (both $p < 0.001$) indicate the curvilinear nature of centralization. In other words, either high or low extremes of centralization undermine the number of shared ideas, although high centralization is more favorable than low centralization. However, centralization has a consistently negative effect on the number of rejected ideas (Table 3).

INSERT TABLE 4 ABOUT HERE

INSERT TABLE 5 ABOUT HERE

The next set of findings explores the creative outcomes of teams. Our second set of propositions (*P1b*, *P2b*) focus on the effect of demography and networks respectively on the creative output of the team. Tables 4 through 7 summarize the regression analyses of the four dependent variables of creative team outcomes (e.g., the number of accepted ideas, recombined idea score, number of functions in the final recombined ideas and aggregate metric measuring creative team potential). Supporting the previous findings for *P1a* and *P2a*, demographic diversity also negatively affects creative production across all regression models at the $p < 0.001$ level and balance has a curvilinear effect on all creative output measures.

Similar to the results of the idea sharing models, tenure diversity again has a positive, statistically significant effect. There is no significance at the $p < 0.05$ level for tenure diversity in the aggregate creative potential. Moreover, the results also support *P1b* in that functional diversity decreases the creative value of the recombined ideas. However, the functional diversity coefficient is positive for the dependent variable measuring the number of functions in the

recombined ideas (Table 6). Following Ancona & Caldwell (1992) who posit that functional diversity has positive effects for innovation, we examine the number of different functions yielded in the produced ideas. Thus, the positive coefficient indicates that increasing functional diversity of the team increases the number of functions recombined in the creative output.

INSERT TABLE 6 ABOUT HERE

INSERT TABLE 7 ABOUT HERE

To further explore the implications of our results on designing the most creative teams, we examine the statistics for the highest performing teams in each of the three categories of assessment, compared with statistics that describe the results of all the experiments. The statistics for the top creative teams are presented in Table 8. The criteria to make the “top” category are different for each statistic, in order to ensure that the outcomes include each observation of that level.

INSERT TABLE 8 ABOUT HERE

Number of ideas is the first assessment of the final product, which varies between 0 and 4, and top performers are considered to be 3 and above. For these teams, we find that racial diversity is lower than average, as is functional diversity. There are also more ideas shared and fewer rejected. The number of functions represented is also slightly higher than average, as are the idea scores and aggregate scores. The lower diversities represented most likely reflect the idea that diversities must be lower in order for more ideas to be shared, and the higher number of functions is also correlated with more ideas. There are, by definition, more ideas required in order to have more functions represented in the final output. And the higher aggregate scores may reflect that having more ideas represented in the final output boosts the aggregate score significantly.

Number of functions represented in the final product shows very similar results, with a few notable exceptions: functional diversity is much higher, which reflects that many functions must be present in order to have many functions in the final product. The aggregate score is also significantly higher than the number of ideas assessment, which confirms that more ideas does not mean that they will all be from different functions – the value of having the same number of ideas from the same function is much lower.

The statistics for creativity score are quite different from number of ideas and number of functions, for some clear reasons. In order for ideas to have a higher creativity score, the expertise and CPS scores of team members must be higher, while the network constraint values must be lower. We also find that racial diversity is higher than the previous two statistics, although it is approximately average. The most interesting finding is that the aggregate score is much lower, which indicates that a output with the highest creativity score occurs when only one idea is shared by a highly creative individual, which is then accepted by the team. This may reflect the existence of creative maverick types like Steve Jobs, and these types are the exceptions, not the rule.

Aggregate score was created to reflect that just having a high score in one of these categories is not enough to ensure a creative output, and was created by multiplying number of ideas, number of functions, and creativity score. We find that overall, having lower racial and gender diversity is important, while higher functional diversity is also important. This enables more ideas to be shared, and less rejected. Unfortunately, the average creativity score is only slightly higher than average, however, the number of functions represented in the idea is much higher.

It is also interesting to compare the number of observations of top performers from each category and to the total number of teams, which was 9600. There were almost 1000 observations of top performers in the number of ideas category, however, when we require that these ideas represent many functions, the number of observations drops to less than 200. The highest creativity scores (≥ 0.75) were only obtained by 275 teams, and those with the highest aggregate scores numbered only 130.

DISCUSSION AND CONCLUSIONS

Adopting a social view of the creative process is influenced by the interactionist framework (Woodman et al., 1993) in that to better explain creative outcomes, we must attend to understanding not just the individual, but also explore how the individual interacts within the group. Thus, to better understand creativity as a social process (Perry-Smith & Shalley, 2012), researchers should examine the social mechanisms of creative teams. Specifically, we posit that the process of idea sharing is the communicative mechanism by which ideas are initially presented and later evaluated for producing creative outcomes. Thus, this paper examines the preliminary stages in which groups begin to recombine ideas. We adopt both theories of team demography and social networks to explain how idea sharing processes are shaped and result in creative outcomes. Instead of adopting one approach exclusively, we incorporate both perspectives to develop a model of idea sharing in creative teams. Whereas prior empirical research has been limited to manipulate team factors in organizational settings, the use of simulation offers opportunities to test hypotheses that would be difficult to do otherwise and explore mechanisms that would be difficult to unpack in the field.

Mechanisms. By focusing on the sociopolitical processes of the team, rather than assume individuals can objectively recognize the inherent creative value of ideas, we present several

mechanisms of how diversity and networks can influence the idea sharing process. As this is a simulation and not an empirical study, we cannot confirm whether our results hold beyond a simulated context; nonetheless, we can validate our model through the replication of previous findings of other researchers. First, we do find a curvilinear effect of our measure of team cohesion. Such curvilinear effects have been found in creativity research with a range of other network factors, such as structural holes (Balkundi et al., 2007) and small world network effects (Uzzi & Spiro, 2005). We also confirm that some types of diversity to lead to diminished creative outputs, although not all types of diversity have the same effect, which leads us to revise our proposition P1a.

Propositions. We posit that mixed findings for P1a (diversity stymies sharing) advocates a more nuanced proposition on diversity's effect on idea sharing. Referring back to Harrison & Klein (2007), not all types of diversity are categorically discrete, like gender, race and function. Rather, diversity that is more continuous in nature – as we see with tenure diversity – can have contrasting effects. We theorize that continuous diversity variables like tenure create greater flexibility for individuals to find commonality with others as opposed to rigid in group versus out group distinctions (Tajfel, 1974). This flexibility in turn increases the probability that two team members would form more ties, thus increasing idea sharing within the team. For example, a group of first and fourth year students may initially form ties among their perspective cohort members, but a group with the same students and tenured faculty may form ties among the students and another subgroup of ties among faculty. Although in the first scenario first and fourth years may see themselves as distinctive subgroups, the second scenario illuminates how continuous diversity attributes are mutable relative to the group. Also, Harrison and Klein

(2007) distinguish between task-related (e.g. tenure and function) and non-task-related (e.g. gender and race), which are likely to influence the social processes of the team in different ways.

Although our simulation does not directly consider task, we do speculate that demographic factors influence the team in different ways, potentially due to the increased flexibility of our task-related demographic characteristics. Thus, we refine P1a as,

P1a': Discrete demographic diversity (e.g., gender, race, function) will stymie the idea sharing process such that team members will share less and have a tendency to reject more ideas.

Implications

Our results also offer pragmatic contributions on how managers should design teams. Based on our results, having creative and expert individuals in the team is not sufficient for producing highly creative ideas. Although our findings suggest diversity reduces the creative value of ideas, we would urge that managers strategically include members who have access to new ideas and different perspectives, but ensure that there is open communication among team members to facilitate the exchange of ideas. Moreover, our findings also suggest there is a centralization “sweet spot” in that a team is optimized for creative outcomes with moderate levels of centralization. For managers, this means to ensure that the relationships among members are mostly balanced, but not completely. In other words, there should be no one prominent individual (an actor with many network ties compared to others in the network) or a team lacking any ties (a network with many isolated members). Moreover, model examples of successful creative teams such as IDEO (Hargadon & Sutton, 1997; Sutton & Hargadon, 1996) reiterate the strategy of diversifying on creativity-related demographics only, while maintaining homogeneity across non-task-related demographics.

Limitations and Future Research

Nonetheless, our study does present some limitations by using simulation, but the limitations of simulation models can offer opportunities for future research. Our model currently has people randomly being the first to share. Other simulation models or studies in the field may find differences if influential people are the first to share and influence how following members share or withhold their ideas. To maintain a parsimonious model, we chose to focus on short term teams, but there may be differences when examining a longer team lifecycle. Additional group processes would add complexity to the model (Taggar, 2001), but nonetheless would be worthwhile for future research. Future research should also investigate when people develop relationships over time within teams; can members begin to evaluate ideas for their inherent creative value or do social forces influence team members to continue evaluating ideas according to the relationships they hold with other members? It is also commonly believed that ideas created by groups are more than the sum of their parts; however, without knowing how much better these ideas will be, we can't take this into account.

Insofar we have discussed how creative teams need individuals to have varied, novel ideas available as resources to recombine and how a social context can be conducive for mutual idea sharing. Although the literature infrequently describes the mechanisms in which ideas come together within teams, we posit that demographic diversity and network configuration of the team can influence the subsequent stages ideas are synthesized into a creative output. The next step of synthesizing ideas would involve different techniques in creative problem solving compared to idea generation and the preliminary evaluation of ideas that we discuss in this paper.

However, we would still expect sociopolitical dynamics to influence communication within the team. Thus, it would be worthwhile to examine how shared demographic attributes and network dynamics influence the team at later stages of the creative process.

In what Lingo and O'Mahony term *nexus work* (2010), brokers do not only transfer ideas, but they also synthesize the ideas from various creators. Our method assumes that teams with a low mean network constraint produce ideas with higher creative value. However, the next step in the creative process would involve investigating how brokers or other team members can synthesize the accepted ideas available for recombination. Future research on recombinant creativity should also attend to how the nexus work of brokers is influenced by sociopolitical nature of teams. For instance, does homophily or tie strength influence the extent to which brokers can integrate ideas from disconnected networks?

In conclusion, we hope that our findings will ignite new hypotheses on idea sharing in creative teams using a variety of methodological approaches. As theories on creative teams adopt a social view of creativity, the literature could benefit from further investigations on the influence of sociopolitical process. Even though we explore the mechanism of idea sharing, other social mechanisms should be explored to help advance our understanding of the creative process.

REFERENCES

- Amabile, T. (1996). *Creativity in context: Update to the social psychology of creativity*. Boulder, CO, USA: Westview Press.
- Amabile, T., & Barsade, S. (2005). Affect and creativity at work. *Administrative Science Quarterly*, 50(3), 367–403.
- Amabile, T. M., Conti, R., Coon, H., Lazenby, J., & Herron, M. (1996). Assessing the work environment for creativity. *Academy of Management Journal*, 39(5), 1154–1184.
- Ancona, D. G., & Caldwell, D. F. (1992). Demography and design: Predictors of new product team performance. *Organization science*, 3(3), 321–341.
- Aral, S., & Van Alstyne, M. (2011). The Diversity-Bandwidth Trade-off. *American Journal of Sociology*, 117(1), 90–171.
- Baer, M., Oldham, G. R., Jacobsohn, G. C., & Hollingshead, A. B. (2008). The Personality Composition of Teams and Creativity: The Moderating Role of Team Creative Confidence. *Journal of Creative Behavior*, 42(4), 255–282.
- Balkundi, P., Kilduff, M., Barsness, Z. I., & Michael, J. H. (2007). Demographic antecedents and performance consequences of structural holes in work teams. *Journal of Organizational Behavior*, 28, 241–260.
- Burt, R. (2004). Structural holes and good ideas. *American journal of sociology*, 110(2), 349–399.
- Burt, R. S., Jannotta, J. E., & Mahoney, J. T. (1998). Personality correlates of structural holes. *Social Networks*, 20(1), 63–87.
- Callaway, M., & Esser, J. (1984). Groupthink: Effects of cohesiveness and problem-solving procedures on group decision making. *Social Behavior and Personality*, 12(2), 157–164.
- Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization science*, 15(5), 555–568.
- Chen, M.-H. (2006). Understanding the Benefits and Detriments of Conflict on Team Creativity Process. *Creativity and Innovation Management*, 15(1), 105–116.
- Cohen, S. G., & Bailey, D. E. (1997). What Makes Teams Work: Group Effectiveness Research from the Shop Floor to the Executive Suite. *Journal of Management*, 23(3), 239–290.
- Coleman, J. (1988). Social capital in the creation of human capital. *American journal of sociology*, 94, S95–S120.
- Csikszentmihalyi, M. (1999). Implications of a Systems Perspective for the Study of Creativity. In R. J. Sternberg (Ed.), *Handbook of creativity* (pp. 313 – 335). Cambridge: Cambridge University Press.
- Diehl, M., & Stroebe, W. (1987). Productivity loss in brainstorming groups: Toward the solution of a riddle. *Journal of personality and social psychology*, 53(3), 497–509.
- Diehl, M., & Stroebe, W. (1991). Productivity loss in idea-generating groups: Tracking down the blocking effect. *Journal of personality and social psychology*, 61(3), 392–403.
- Drazin, R., Glynn, M. A., & Kazanjian, R. K. (1999). Multilevel Theorizing about Creativity in Organizations: A Sensemaking Perspective. *Academy of Management Review*, 24(2), 286–307.
- Fleming, L. (2001). Recombinant uncertainty in technological search. *Management science*, 47(1), 117–132.
- Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52, 443–475.

- Gargiulo, M., & Benassi, M. (2000). Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital. *Organization science*, 11(2), 183–196.
- Gough, H. (1979). A creative personality scale for the Adjective Check List. *Journal of Personality and Social Psychology*, 37(8), 1398–1405.
- Granovetter, M. (1973). The strength of weak ties. *American journal of sociology*, 78(6), 1360–1380.
- Hargadon, AB, & Bechky, B. (2006). When collections of creatives become creative collectives: A field study of problem solving at work. *Organization Science*, 17(4), 484–500.
- Hargadon, Andrew, & Sutton, R. (1997). Technology brokering and innovation in a product development firm. *Administrative science quarterly*, 42(4), 716–749.
- Harrison, D. a., & Klein, K. J. (2007). What's the Difference? Diversity Constructs As Separation, Variety, or Disparity in Organizations. *Academy of Management Review*, 32(4), 1199–1228.
- Harrison, D., & Klein, K. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, 32(4), 1199–1228.
- Harrison, J., Carroll, G., & Carley, K. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, 32(4), 1229–1245.
- Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, 9–30.
- Janis, I. (1972). *Victims of groupthink: A psychological study of foreign-policy decisions and fiascoes*. Boston: Houghton Mifflin.
- Kurtzberg, T., & Amabile, T. (2001). From Guilford to creative synergy: Opening the black box of team-level creativity. *Creativity Research Journal*, 13(3 & 4), 285 – 294.
- Lazer, D., & Friedman, A. (2007). The Network Structure of Exploration and Exploitation. *Administrative Science Quarterly*, 52, 667–694.
- Lingo, E. L., & O'Mahony, S. (2010). Nexus Work: Brokerage on Creative Projects. *Administrative Science Quarterly*, 55(1), 47–81.
- Macy, M. W., & Willer, R. (2002). From Factors to Actors: Computational Sociology and Agent-Based Modeling. *Annual Review of Sociology*, 28(1), 143–166.
- Mannix, E., & Neale, M. A. (2005). Differences Make Difference? What The Promise and Reality of Diverse Teams in Organizations. *Psychological Science in the Public Interest*, 6(2), 31–55.
- Martins, L. L., & Shalley, C. E. (2011). Creativity in Virtual Work: Effects of Demographic Differences. *Small Group Research*, 42(5), 536–561.
- Mollica, K., & DeWitt, R. (2000). When Others Retire Early: What About Me? *Academy of Management Journal*, 43(6), 1068–1075.
- Monge, P. R., & Contractor, N. S. (2003). *Theories of Communication Networks*. Oxford University Press.
- Mueller, J. S., Melwani, S., & Goncalo, J. a. (2012). The bias against creativity: why people desire but reject creative ideas. *Psychological science*, 23(1), 13–17.
- Murray, F., & O'Mahony, S. (2007). Exploring the Foundations of Cumulative Innovation: Implications for Organization Science. *Organization Science*, 18(6), 1006–1021.
- Oldham, G., & Cummings, A. (1996). Employee creativity: Personal and contextual factors at work. *Academy of management journal*, 39(3), 607–634.

- Paulus, P. B., & Yang, H.-C. (2000). Idea Generation in Groups: A Basis for Creativity in Organizations. *Organizational Behavior and Human Decision Processes*, 82(1), 76–87.
- Perry-Smith, J. E. (2006). Social Yet Creative: The role of social relationships in facilitating individual creativity. *The Academy of Management Journal*, 49(1), 85–101.
- Perry-Smith, J. E., & Shalley, C. E. (2003). The Social Side of Creativity: A Static and Dynamic Social Network Perspective. *The Academy of Management Review*, 28(1), 89–106.
- Perry-Smith, J. E., & Shalley, C. E. (2012). The Social Side of Creativity: A static and dynamic social perspective. *Academy of Management Review*, 28(1), 89–106.
- Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda. *Journal of Management*, 38(4), 1115–1166.
- Reagans, R., Zuckerman, E., & McEvily, B. (2004). How to Make the Team: Social Networks vs. Demography as Criteria for Designing Effective Teams. *Administrative Science Quarterly*, 49(1), 101–133.
- Richardson, G. P. (2001). System Dynamics. In S. Gass & C. Harris (Eds.), *Encyclopedia of Operations Research and Management Science* (pp. 807 – 810). Kluwer Academic Publishers.
- Sosa, M. E., & Mihm, J. (2008). *Organization design for new product development. Handbook of new product development management* (pp. 165–198).
- Sutton, R., & Hargadon, A. (1996). Groups in Brainstorming Context : Effectiveness in a Product Design Firm, *41*(4), 685–718.
- Taggar, S. (2001). Group Composition, Creative Synergy, and Group Performance. *The Journal of Creative Behavior*, 35(4), 261–286.
- Tajfel, H. (1974). Social identity and intergroup behaviour. *Social Science Information/sur les sciences sociales*, 13(2), 65–93.
- Tajfel, H., & Turner, J. (1979). *An integrative theory of intergroup conflict. ... social psychology of intergroup ...* London and New York: Published in cooperation with European Association of Experimental Social Psychology by Academic Press.
- Uzzi, B., & Spiro, J. (2005). Collaboration and Creativity: The Small World Problem. *The American Journal of Sociology*, 111(2), 447–504.
- Vincent, A., Decker, B., & Mumford, M. (2002). Divergent thinking, intelligence, and expertise: A test of alternative models. *Creativity research journal*, 14(2), 37–41.
- Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*.
- Wilensky, U. (1999). NetLogo. Evanston, IL: Center for Connected Learning and Computer-Based Modeling, Northwestern University. Retrieved from <http://ccl.northwestern.edu/netlogo/>
- Williams, K. Y., & O'Reilly, C. A. (1998). Demography and Diversity in Organizations. *Research in Organizational Behavior*, 20, 77–140.
- Woodman, R., Sawyer, J., & Griffin, R. (1993). Toward a theory of organizational creativity. *Academy of management review*.

FIGURES AND TABLES

FIGURE 1. Theoretical Framework

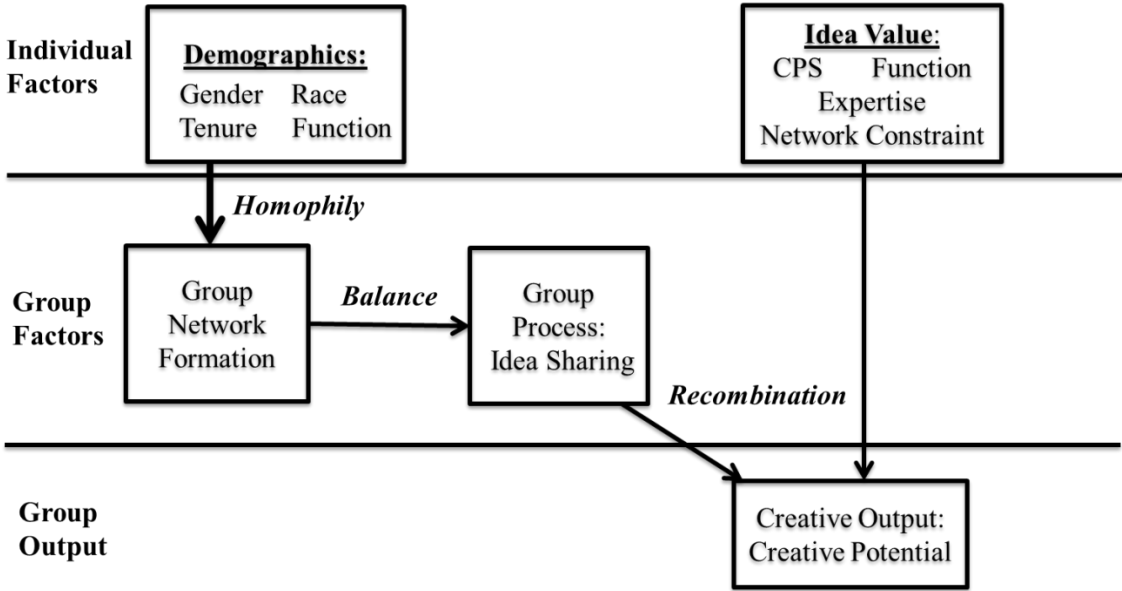


TABLE 1. Summary of diversity metrics

Parameter Settings			
Parameter	Variable	Range	Model Settings⁴
Team size	$ T $	2 – 10	4
Number of female	gen	0 – $ T $	0,1,2
Number of races	$race$	1 – $ T $	1,2,3,4
Number of functions	fun	1 – $ T $	1,2,3,4
Tenure	ten	$ten \sim U(0,30)$	0 – 30
Network Constraint	nc	$nc \sim U(0,100)$	0 – 100
Expertise	exp	$exp \sim U(0,30)$	0 – 30
Creative Personality Score (CPS)	cps	$cps \sim U(0,30)$	0 – 30
Diversity Calculations			
Variable	Metric	Formula	
Gender		$D_{gen} = 1 - p_f^2 - p_m^2$	
Function	Blau's Index	$D_{func} = 1 - \sum_{f \in F} p_f^2$	
Race		$D_{race} = 1 - \sum_{r \in R} p_r^2$	
Tenure	Coefficient of Variation	$D_{ten} = \sigma_{ten} / \mu_{ten}$	
Expertise		$D_{exp} = \sigma_{exp} / \mu_{exp}$	
Network Diversity	Centralization	$D_{net} = \frac{\sum_{j \in T} [\max_{i \in T} (wdc_i) - wdc_j]}{(T - 1)(T - 2)}$	

⁴ With all of the settings, there were 48 different combinations to test, and we ran 200 simulations at each setting, resulting in 9600 observations

Table 2. Effect of Demographic Diversity and Network Variables on Number of Shared Ideas

	Model 1	Model 2	Model 3
Mean Team CPS	-0.009 (.163)	-0.066 (0.161)	-0.064 (0.161)
Mean Team Expertise	-0.080 (0.161)	-0.054 (0.159)	-0.054 (0.159)
Gender	0.027 (0.033)		0.077* (0.033)
Racial/Ethnic	-0.086*** (0.025)		-0.0782** (0.025)
Tenure	0.112*** (0.025)		0.107*** (0.025)
Functional	-0.090*** (0.025)		-0.0686** (0.025)
Centralization		1.991*** (0.346)	2.015*** (0.346)
Centralization ²		-9.837*** (0.992)	-9.882*** (0.993)
Network Constraint		-0.069 (0.048)	-0.071 (0.048)
Constant	2.248*** (0.042)	2.270*** (0.049)	2.247*** (0.054)
N	9600	9600	9600
R ²	0.005	0.033	0.037
Adjusted R ²	0.004	0.033	0.036
F	7.257	55.49	35.31

Robust errors reported in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 3. Effect of Demographic Diversity and Network Variables on Number of Rejected Ideas

	Model 1	Model 2	Model 3
Mean Team CPS	0.137 (0.182)	0.0439 (0.191)	0.0303 (0.178)
Mean Team Expertise	-0.218 (0.182)	-0.252 (0.195)	-0.209 (0.179)
Gender	0.545*** (0.037)		0.647*** (0.036)
Racial/Ethnic	0.648*** (0.027)		0.677*** (0.026)
Tenure	0.0039 (0.030)		-0.0063 (0.029)
Functional	0.680*** (0.027)		0.721*** (0.026)
Centralization		-0.802* (0.332)	-1.478*** (0.311)
Centralization ²		-2.580** (0.953)	-1.997* (0.899)
Network Constraint		0.0170 (0.059)	0.0198 (0.054)
Constant	0.151*** (0.046)	1.115*** (0.056)	0.374*** (0.057)
N	9600	9600	9600
R ²	0.124	0.026	0.167
Adjusted R ²	0.123	0.026	0.166
F	267.2	56.33	235.4

Robust errors reported in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 4. Effect of Demographic Diversity and Network Variables on Number of Accepted Ideas

	Model 1	Model 2	Model 3
Mean Team CPS	-0.146 (0.197)	-0.110 (0.211)	-0.0945 (0.200)
Mean Team Expertise	0.138 (0.197)	0.198 (0.212)	0.155 (0.196)
Gender	-0.519*** (0.040)		-0.569*** (0.040)
Racial/Ethnic	-0.733*** (0.030)		-0.755*** (0.030)
Tenure	0.109*** (0.032)		0.113*** (0.031)
Functional	-0.770*** (0.031)		-0.789*** (0.030)
Centralization		2.793*** (0.355)	3.493*** (0.332)
Centralization ²		-7.257*** (1.050)	-7.885*** (1.005)
Network Constraint		-0.0855 (0.064)	-0.0905 (0.059)
Constant	2.096*** (0.051)	1.155*** (0.061)	1.873*** (0.063)
N	9600	9600	9600
R ²	0.129	0.008	0.144
Adjusted R ²	0.128	0.007	0.143
F	241.9	13.81	190.4

Robust errors reported in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 5. Effect of Demographic Diversity and Network Variables on Idea Score

	Model 1	Model 2	Model 3
Mean Team CPS	0.884*** (0.051)	0.894*** (0.051)	0.897*** (0.049)
Mean Team Expertise	0.923*** (0.051)	0.946*** (0.051)	0.939*** (0.050)
Gender	-0.0996*** (0.010)		-0.116*** (0.010)
Racial/Ethnic	-0.104*** (0.007)		-0.111*** (0.007)
Tenure	0.0168* (0.008)		0.0192* (0.008)
Functional	-0.112*** (0.007)		-0.119*** (0.007)
Centralization		0.812*** (0.092)	0.926*** (0.089)
Centralization ²		-1.794*** (0.262)	-1.888*** (0.253)
Network Constraint		-0.271*** (0.015)	-0.272*** (0.015)
Constant	0.252*** (0.013)	0.196*** (0.015)	0.309*** (0.016)
N	9600	9600	9600
R ²	0.102	0.100	0.150
Adjusted R ²	0.101	0.099	0.150
F	207.8	213.2	216.8

Robust errors reported in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 6. Effect of Demographic Diversity and Network Variables on Number of Functions Represented in Accepted Ideas

	Model 1	Model 2	Model 3
Mean Team CPS	-0.066 (0.144)	-0.0482 (0.148)	-0.0363 (0.144)
Mean Team Expertise	0.155 (0.145)	0.191 (0.150)	0.166 (0.145)
Gender	-0.287*** (0.030)		-0.316*** (0.030)
Racial/Ethnic	-0.381*** (0.022)		-0.394*** (0.022)
Tenure	0.0654** (0.024)		0.0678** (0.024)
Functional	0.244*** (0.020)		0.233*** (0.020)
Centralization		2.038*** (0.250)	2.285*** (0.244)
Centralization ²		-5.014*** (0.722)	-5.415*** (0.708)
Network Constraint		-0.0389 (0.045)	-0.0348 (0.044)
Constant	1.077*** (0.035)	0.827*** (0.043)	0.925*** (0.045)
N	9600	9600	9600
R ²	0.051	0.009	0.063
Adjusted R ²	0.051	0.008	0.062
F	85.08	15.32	73.26

Robust errors reported in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 7 Effect of Demographic Diversity and Network Variables on Aggregate Creative Team Potential

	Model 1	Model 2	Model 3
Mean Team CPS	4.596*** (0.194)	4.604*** (0.189)	4.610*** (0.187)
Mean Team Expertise	4.800*** (0.200)	4.887*** (0.196)	4.874*** (0.194)
Gender	-0.227*** (0.040)		-0.260*** (0.038)
Racial/Ethnic	-0.190*** (0.028)		-0.204*** (0.027)
Tenure	0.0149** (0.030)		0.0228** (0.029)
Functional	-0.214*** (0.029)		-0.231*** (0.028)
Centralization		1.845*** (0.304)	2.074*** (0.298)
Centralization ²		-4.223*** (0.888)	-4.401*** (0.876)
Network Constraint		-1.421*** (0.057)	-1.422*** (0.057)
Constant	-0.264*** (0.050)	0.0317 (0.053)	0.263*** (0.059)
N	9600	9600	9600
R ²	0.120	0.168	0.182
Adjusted R ²	0.120	0.168	0.181
F	195.1	303.0	200.1

Robust errors reported in parentheses

* p<0.05, ** p<0.01, *** p<0.001

TABLE 8. Comparison of the top categories of each idea assessment metric with descriptive statistics

Statistics	Recombination output statistics				Experiment statistics		
	Number of Ideas	Number of Functions	Creativity Score	Aggregate Score	Min	Mean	Max ⁵
Mean Expertise	14.47	14.85	17.39	15.77	1.00	14.50	28.25
Mean CPS Score	14.36	14.65	17.11	15.67	0.75	14.57	27.75
Mean Network Constraint	0.49	0.50	0.41	0.45	0.05	0.49	0.93
Gender Diversity	0.25	0.25	0.28	0.25	0	0.29	0.50
Racial Diversity	0.32	0.32	0.46	0.32	0	0.45	0.75
Tenure Diversity	0.64	0.64	0.61	0.64	0	0.62	2.00
Centralization	0.14	0.13	0.14	0.13	0	0.15	0.42
Functional Diversity	0.30	0.73	0.44	0.72	0	0.45	0.75
Ideas Shared	3.02	3.05	2.11	3.05	0	2.23	4
Ideas Rejected	0.01	0.05	0.89	0.03	0	0.90	4
Number of Ideas	3.01	3.01	1.21	3.02	0	1.33	4
Number of Functions	1.55	3.01	1.05	2.95	0	0.98	4
Idea Score	49.33	49.33	80.63	54.37	0	39.84	95.67
Aggregate Score	2.30	4.46	1.06	4.81	0	0.86	6.41
"Top" Criteria	≥ 3	≥ 3	≥ 0.75	$\geq 4^6$			
Number of Observations	993	170	275	130			

⁵ Minimum and maximum values here are from actual observations, not the possible values based on the model settings, although in some cases these are the same.

⁶ If we set the minimum aggregate as the product of the criteria for the other three categories, the criteria would be ≥ 6.75 ($3 * 3 * 0.75$), however, none of the aggregate scores exceed 6.41, so it is not possible to obtain the highest values of each statistic at the same time.

