

The microdynamics of team diversity and collaboration networks

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A dissertation

submitted in partial fulfillment of the  
requirements for the degree of

Doctor of Philosophy

University of Washington

2018

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Program Authorized to Offer Degree:

Business Administration

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**Abstract**

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Current team diversity research is largely equivocal regarding the direct effects of intrateam differences on team processes and performance. In response, scholars encourage a more complex and multi-level approach to understanding this phenomenon. In this dissertation, I contribute to this effort by theorizing an emergent network approach to team diversity—that is, a dynamic, relational and structural approach to interpersonal differences. Given the historical and current emphasis on collective-level theories and measures of diversity in the team literature, I argue that this perspective will provide a more detailed account of the perceptions and behaviors associated with differences within teams. Through this paradigm, I ask two interrelated research questions. First, how does the structure of team diversity impact dyadic task-related collaboration over time within the team? Second, how does the heterogeneity of dyadic collaboration affect team performance? These questions are tested with a combination of archival and laboratory data using stochastic actor-oriented models (SAOMs), which enables the prediction of network evolution over time.

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## INTRODUCTION

The systematic study of diversity in teams is both critically important and excruciatingly complex. Teams are the *de facto* organizing mechanism for modern organizations, and an increasingly global economy focused on collaborative knowledge work means that these teams are also increasingly heterogeneous both in terms of demographic variables as well as knowledge, skills and abilities (Mathieu, Tannenbaum, Donsbach, & Alliger, 2014). However, a substantial number of qualitative reviews (Jackson, Joshi, & Erhardt, 2003; Joshi, Liao, & Roh, 2011; Meyer, Glenz, Antino, Rico, & González-Romá, 2014; van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998) and meta-analyses (Horwitz & Horwitz, 2007; Joshi & Roh, 2009; van Dijk, van Engen, & van Knippenberg, 2012) of team diversity highlight an inconclusive trend of findings that finds divergent results for the impact of team diversity on team processes and team performance.

Scholars have responded to the equivocality of results in the diversity literature with several calls to extend our collective knowledge in this field. In their review of the diversity literature, van Knippenberg and Schippers declared “the bankruptcy of direct effects models” and called for models of team diversity that explicate more of the underlying processes and take into account more of the complex contingencies that determine the outcomes from diverse teams (van Knippenberg & Schippers, 2007). Some have encouraged looking at more macro-level of analysis, where factors such as organizational or national context, that might impact the relationship between team diversity and performance (Jackson et al., 2003; Joshi et al., 2011; Joshi & Roh, 2009), while others have adopted a more micro approach by looking at the role of dyadic and individual processes in a team (Aime, Humphrey, DeRue, & Paul, 2014; Humphrey & Aime, 2014; Joshi, 2014; Joshi & Knight, 2015). Still others have lamented the imbalance

between longitudinal theory and longitudinal empirical work, noting that our conceptual frameworks regarding how teams function over time far outstrip our empirical knowledge (Mathieu et al., 2014).

These various calls can be summarized with two basic statements. First, teams are not static entities, and thus deserve to be studied in a longitudinal and dynamic manner (Arrow, McGrath, & Berdahl, 2000; Cronin, Weingart, & Todorova, 2011; Mathieu, Maynard, Rapp, & Gilson, 2008; Mathieu et al., 2014). We have theory to address how teams form, develop, and change—but we have relatively sparse data to robustly support or dispute these theories. The reasons that theory precedes empirical work are obvious, a primary one being the complexity of collecting team data over time. Additionally, the analytical methods needed to analyze these longitudinal data are often advanced and not typically part of a management researcher's toolkit. However, we need to understand the role of time in teams to truly understand the nature of teamwork and other interdependent processes that are the foundational rationale for teaming in the first place.

Second, teams are not simple collectives, but are instead complex combinations of interdependent relationships, and thus deserve to be studied in a more precise manner than just simple individual/collective (Arrow et al., 2000; Bavelas, 1950; Gittell, 2011; Humphrey & Aime, 2014; Joshi & Knight, 2015). It is no small irony that this was an emphasis of early teams researchers as done by Bavelas, who used early network concepts to determine which small group communication patterns yielded the best performance (Bavelas, 1950). However, the bulk of social network research moved into sociologically-oriented fields in the 1960s and 1970s, while those working at the micro level predominantly chose an individuals-within-collectives paradigm for understanding teams and their processes (Katz, Lazer, Arrow, & Contractor, 2004;

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Prell, 2012). Research on within-team networks is seeing a new resurgence in the last two decades (Katz, Lazer, Arrow, & Contractor, 2005), combining the interdependent approach of team networks with theories that were previously focused on the individual or collective level.

The combination of these two concepts within teams—time and networks—points to a paradigm of network *evolution* within teams. This dissertation builds from this basic idea, viewing teams as dynamic networks of members whose relationships have implications for individual-, dyadic-, and team-level outcomes. These ideas can be represented through three interrelated research questions. First, what impact does the structure of team diversity—defined broadly as the arrangement of relative dyadic differences or similarities between members on the team—have on dyadic task-related collaboration within the team? Second, do early (and potentially biased) patterns of collaboration fade over time, giving way to a pattern of interaction that is optimized for performance? Allport’s “contact hypothesis” (1954) suggests the former, but several team development theories suggest that early events embed particular patterns of engagement into the long-term rhythm of the team (Mathieu et al., 2014)—and thus early biases towards working with similar others could persist. Finally, how does the nature of dyadic collaboration affect team performance? I will argue that, while interpersonal differences tend to weakly reduce dyadic collaboration, the teams that do manage to collaborate across these differences are the best performers. These hypotheses are specifically aimed at highly interdependent settings, as the meta-analytic evidence clearly points at task type being an important moderator of diversity’s downstream effects (Joshi & Roh, 2009; van Dijk et al., 2012).

The following dissertation will consist of three primary chapters. The first chapter will be a literature review, providing a brief historical overview of the team diversity literature and

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contrasting it with one that takes a network perspective. The second chapter (which is currently under second round review at *Academy of Management Review*) will develop a theoretical model based on an emergent network approach, which I argue can clarify some of the ambiguity in more traditional paradigms. Finally, in the third chapter uses a combination of archival and laboratory data to test a fundamental set of propositions from this emergent network theory—that heterogeneous collaboration partnerships have performance implications for teams.

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## **CHAPTER 1: PERSPECTIVES ON TEAM DIVERSITY**

The last two decades have seen many researchers attempt to reconcile conflicting results in the team diversity literature via qualitative reviews (Jackson, Joshi, & Erhardt, 2003; Joshi, Liao, & Roh, 2011; Meyer, Glenz, Antino, Rico, & González-Romá, 2014; van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998) and meta-analyses (Horwitz & Horwitz, 2007; Joshi & Roh, 2009; van Dijk, van Engen, & van Knippenberg, 2012). Each of these reviews highlights different aspects of the relationship of team diversity with team processes and performance, but the overall findings are muddled and largely inconclusive. My fundamental argument is that these ambiguous findings are at least partially a result of focusing attention on team-level concepts of diversity, rather than recognizing it as a relational, structural and dynamic phenomenon—that is, an emergent network. In order to build a foundation for this network-oriented approach to team diversity, I will briefly review the prior literature on team diversity.

### **PRIOR LITERATURE ON TEAM DIVERSITY AND PERFORMANCE**

#### **Efforts via diversity dimension typologies**

While neither the first nor the most complete review of the diversity literature, the early work by Milliken and Martins (1996) is notable for describing diversity as a “double-edged sword, increasing the opportunity for creativity as well as the likelihood that group members will be dissatisfied and fail to identify with the group” (Milliken & Martins, 1996, p. 403). This idea that team diversity can create opposing effects is echoed in much of the work that follows. Milliken and Martins attributed this primarily to a distinction between observable versus underlying differences, arguing that demographic diversity categorically tends to lead to lower team integration and higher likelihood of factions while skill or knowledge diversity naturally increases the quantity of information and perspectives available to the group as a whole.

The qualitative review by Williams and O'Reilly (1998) is considered by many scholars to be a watershed effort (van Knippenberg & Schippers, 2007), as it reviewed the literature over a forty-year span—arguably the chronological extent of modern diversity research at the time. This consisted of eighty-eight articles (fifty-seven of which were published after 1990) and covered diversity at both the organizational and team/group level, although the vast majority of the findings (and theory) are focused on the more proximal workgroup. Importantly, Williams and O'Reilly identified three major theoretical assumptions for studies investigating describing the effects of diversity on process and performance. First, scholars theorizing the benefits of diversity would often use information processing as a theoretical framework with the idea that unique information provides a deeper knowledge base for use in the group. Second, researchers often invoked social identity theory (Tajfel, 1982) to describe the limiting effects of team diversity on processes and performance, since social categorization and intergroup bias creates a disinclination to work with individuals perceived as different. Finally, the similarity/attraction hypothesis (Byrne, 1971, 1997) suggests people prefer to work with similar others. While the latter two theories were generally used to generate the same hypothesized negative prediction regarding diversity and team performance, Williams and O'Reilly pointed out an issue with this tendency and called for more explicit tests of mediating mechanisms to clarify theory:

*“...although similar in some respects, similarity/attraction and social categorization theories make somewhat different assumptions about the effects of diversity on groups. Similarity/attraction theory predicts that increased similarities between an in-group and an out-group should increase liking and decrease conflict. However, social identity theory suggests that if members of two groups perceive themselves to be more similar, they are likely to derogate each other even more in an effort to maintain their self-esteem*

*through their in-group status. Since variations in the demographic composition of groups are complex, research must provide insight into the interactions among many types of diversity, informational contributions, and situational moderators...*” (Williams & O’Reilly, 1998, pp. 117–118)

A primary theme coming out of both of these reviews was one of a typology of diversity dimensions that lead to divergent processes, echoing the earlier statements by Milliken and Martins (1996). This question of “good” diversity versus “bad” diversity has played a major role in the scholarly discussion since Williams and O’Reilly (1998), and was also fundamental in the ideas of other researchers (cf. Harrison, Price, & Bell, 1998; Pelled, 1996). Two meta-analyses appear to support this idea. First, Horwitz and Horwitz (2007) directly investigated this split between bio-demographic diversity and task-related diversity, hypothesizing positive results for both with the latter being a stronger effect. Their results, using 35 articles from 1985–2006, supported the positive correlation for task-related diversity and performance but not for bio-demographic diversity (implicitly supporting the “stronger effect” hypothesis). Second, the meta-analysis by Joshi and Roh (2009), while primarily designed to examine the moderating role of context in the diversity–performance relationship, also split the demographic dimensions. Their analysis supported the work echoed that of other scholars—that the general direct effect of team diversity on team performance is negligible—but there were small and significant effects when diversity “bundles” were created by combining diversity into task (positive effect) and relational (negative effect) bundles.

In contrast to this, I would argue for a dimension-free theory of diversity—at least at a general level. Despite the findings and theory that seemingly support the idea of a clearly delineated split between demographic and job-related diversity, there is reason to take these

results with a fair amount of skepticism. First, the Horwitz and Horwitz (2007) study looks at a very small number of studies, particularly given the time frame covered. For a similar span of time—but one in which much less work was actually available—the Williams and O'Reilly (1998) qualitative review covered more than twice as many studies. Second, the results in the Joshi and Roh (2009) review are driven by one strong dimension in each category. For task-oriented diversity (i.e. job-related diversity), only functional diversity was significantly and positively related to performance while education and tenure were not. For relations-oriented diversity (i.e. demographic diversity), only age was significantly and negatively related to performance while race/ethnicity and gender were not. This indicates less of a “cluster effect”, and more of an individual dimension effect in the studies analyzed ( $n = 39$ ).

In addition, some scholars question the very concept of this seemingly intuitive distinction, noting that dimensions do not cleanly fall into beneficial and detrimental categories. Demographic (or surface-level) dimensions are often used as proxies for attitudinal differences (Harrison et al., 1998), which indicates their downstream effects on behavior may be more correlated than orthogonal. Further, van Knippenberg and colleagues note that demographic differences can be sources of unique information and informational differences can generate social categorization processes (van Knippenberg, De Dreu, & Homan, 2004), which is in opposition to the dimensional bundles idea.

As a quantitative test of this line of reasoning, van Dijk and colleagues re-analyzed studies included in both Horwitz & Horwitz (1997) and Joshi & Roh (2009) but included research design moderators such as performance rating source and objective versus subjective performance measures (van Dijk et al., 2012). This analysis revealed that the majority of variance attributed to diversity dimensions in past literature could be attributable to

methodological artifacts related to the use of subjective (leader-rated) performance. In other words, the same implicit bias that diversity researchers are often interested in could be driving the supervisor ratings of performance that are used to validate their research claims. For these reasons, my theorizing will continue by considering differences.

### **Efforts via theoretical complexity: Categorization-Elaboration Model**

Moving past simple dichotomies of diversity dimensions, researchers in the past decade are increasingly acknowledging the inherently complex nature of diversity. A main critique of older models of team diversity is the existence of “too much ad hoc theorizing and too little development of theoretical frameworks that are more widely applied in the study of diversity...[and] the lack of empirical attention to the processes that are presumed to underlie the effects of diversity” (van Knippenberg & Schippers, 2007, p. 533). While Williams and O’Reilly identified three clear theoretical processes that undergird extant theory on the relationship between team diversity and team performance—social categorization, similarity/attraction, and information processing—they also noted that we knew little about how those actually functioned because they were rarely operationalized in empirical studies (Williams & O’Reilly, 1998). Thus, one method of approaching diversity’s multi-faceted nature is by further explicating these “theorized but not measured” aspects of diversity. This moves the field away from the “bankruptcy of the direct effects approach” (van Knippenberg & Schippers, 2007) by adding both explanatory mechanisms (mediators) and contingencies (moderators) into the equation.

The Categorization–Elaboration Model (CEM; van Knippenberg et al., 2004; van Knippenberg & van Ginkel, 2010) is an important example of this approach. Here, the authors argue that researchers in the competing theoretical streams tend to examine their focal outcome as though it existed in isolation, even though concepts like team diversity are complex and

interactive processes (van Knippenberg et al., 2004). Social categorization researchers, in accordance with that camp's theory on intergroup competition and bias, see diversity primarily as a source of factions and conflict, and which logically leads to a degradation of team processes and performance. Conversely, information-sharing and decision-making scholars focus on the task-oriented positive performance effects of the amount of unique information that can be contained within the group. From this perspective, it logically follows more information diversity within the team will lead to better team performance.

Van Knippenberg and colleagues argue that no modeling of team diversity effects is complete without accounting for both theoretical perspectives (information sharing and social categorization) mentioned above. Both effects are expected to happen simultaneously and therefore should affect one another. For this reason, they theorize an interactive model of team diversity, in which both the benefits and disadvantages of diversity can be simultaneously accounted for (van Knippenberg et al., 2004). The authors theorize that team diversity's relationship with team performance is mediated by information sharing and elaboration processes. Simultaneously, team diversity can lead to social categorization and intra-team, intergroup biases that negatively moderate the positive effects of information elaboration. Thus, the authors suggest a reinterpretation of the underlying processes of team diversity as being interactive rather than just opposing or additive. In other words, information processing and social categorization co-determine the impact of team diversity on performance.

This concept of simultaneous and combined processes stemming from diversity becomes important when considering the role of time and dynamic development of states and processes such as trust or collaboration. Although theorizing of the CEM is relatively silent on longitudinal issues, van Knippenberg and colleagues do note that there are different temporal

elements related with the different processes. Social categorization could be conceived as being an early process, with information sharing happening later—but time could also reveal previously-hidden differences that create further categorization and limit information elaboration (van Knippenberg et al., 2004). Thus, the impact of time on the CEM is somewhat ambiguous and requires more detailed examination. (A discussion of the role of time in the diversity-outcome relationship will be handled in a subsequent section.)

### **Efforts via methodological clarity**

Concurrent to calls from researchers like van Knippenberg and colleagues for more theoretical complexity, other scholars have noted the need for more methodological clarity in our investigation of team diversity outcomes. One example of this was described in detail by Harrison and Klein (2007), who noted that diversity is a complex and multi-faceted concept which is not neatly captured with a single measure. Instead, Harrison and Klein delineate three different “forms” of diversity and outline different measurement techniques for each. The first is separation, which is best thought of as differences between group members on dimensions that do not have an explicit rank order (e.g. values, beliefs, attitudes). The second diversity concept is that of variety, which describes group differences based on backgrounds, information sources, or relevant training (e.g. functional background, content expertise, work experience). Lastly, disparity describes resource differences between group members regarding criteria that are explicitly ranked or have a quantifiable relevance (e.g. salary, power, status, decision-making authority).

These distinctions in diversity operationalization become particularly important when theorizing how diversity relates to outcomes. For example, the creativity literature would consider increased information diversity to be positively related to improved ideation in groups.

This diversity is not a function of disparity (e.g. power or salary differences) or separation (e.g. value-based differences), but rather the variety of functional background, training, and work experience residing in the group. Conversely, the conflict literature would more typically view diversity from its tendency to generate splits within the group, aligning more with the concepts of disparity or separation diversity.

It is important to note that Harrison and Klein consider demographic criteria to be usable in any one of the three diversity definitions, depending on the context. This resembles statements made by other researchers (van Dijk et al., 2012; van Knippenberg et al., 2004) acknowledging that the nature of diversity dimensions themselves (e.g. job-related versus demographic) should not be considered as a source of differentiating effects. Just as demographic differences can lead to positive or negative effects on group performance, they can be viewed through any of the operational approaches of Harrison and Klein.

The important differentiation between these forms of diversity happens not at points of minimal heterogeneity (homogeneity), but at maximal heterogeneity. In the former case, each concept looks quite similar—agreement or convergence of team members. However, in the latter scenario, each conceptualization of diversity has a different maximizing distribution. The concept of separation is maximally diverse when two equally strong groups form at opposing ends of a value spectrum—in essence, an extreme bimodal distribution. Variety is maximally diverse when all members differ from one another on the criterion of evaluation, or a low and flat distribution (one case per category). Diversity on a disparity level is maximized when one person holds all of the resources in question while the rest of the group has virtually nothing, creating a strong skew in the distribution of the attribute in question.

**Efforts via theoretical complexity: Faultlines and subgroups**

Closely related to Harrison and Klein's (2007) concept of separation in which groups split into opposing factions, faultlines and subgroups are increasingly being used to describe the overall diversity of teams and the interactions between their members. Faultlines are hypothetical divisions within the boundaries of a group based on the group-level structure of differences between individuals (Bezrukova, Jehn, Zanutto, & Thatcher, 2009; Jehn, 1995; Jehn & Bezrukova, 2010; Lau & Murnighan, 1998, 2005; Mäs, Flache, Takács, & Jehn, 2012; Thatcher & Patel, 2011, 2012). While these divisions are often implicit, triggering events can make these boundaries salient. In their inductive qualitative study, Chrobot-Mason and colleagues identified five categories of triggering events: (1) *assimilation* attempts by the group majority, (2) *differential treatment* based on dormant faultline characteristics, (3) a clash of *different values*, (4) an *insult or humiliating action* from one group to another, and (5) *simple contact* across dormant faultlines (Chrobot-Mason, Ruderman, Weber, & Ernst, 2009). When dormant faultlines are "activated", they can draw attention away from the primary task of the group by generating intergroup relational conflict and dissent.

A related notion is that of team subgroups (Carton & Cummings, 2012, 2013; Meyer et al., 2014). While faultlines focus on the possible splits between members of the larger group, subgroup theory focuses on the intergroup functioning of the clusters that are derived from a split. Also, faultline theory is relatively neutral regarding the effects of specific diversity dimensions (as I argued early), while subgroup theory builds on prior theory (Harrison & Klein, 2007) postulates that subgroup functioning and inter-subgroup relations will differ based on the type of dimensions that were the source of the originating faultline (Carton & Cummings, 2012). Subgroup theory generally asserts that the effects of (1) identity-based subgroups will be largely negative, (2) knowledge-based subgroups will be largely positive, and (3) resource-based

subgroups will be mixed. However, it is theoretically acknowledged that any particular dimension can generate any of these subtypes (identity-, knowledge- or resource-based).

An important observation for a network-based view of diversity is that the theorized impact of diversity dimensions is highly contingent upon structural characteristics such as subgroup size and configuration (Carton & Cummings, 2013). This lends credence to the idea that arrangement of attributes in general is more predictive of team outcomes than the simple presence or absence of difference along a particular dimension. It is also noteworthy that dyadic ties themselves play a relatively unimportant role in these theories, except as a way to derive the larger group-level structure of differences. While some studies look at the effects of members that somehow bridge the subgroup divide (Ren, Gray, & Harrison, 2014), the concepts of faultlines and subgroups are still a primarily group-level phenomenon. The subgroup algorithm used by Carton and Cummings (Carton & Cummings, 2013) uses dyadic interpersonal differences in a broad sense to generate likely subgroupings, but it stops short of looking at micro-structures of multiple dyads to predict relationships between individuals. If these subgroupings are evaluated at the dyadic level as Carton and Cummings suggests, then perhaps it is more useful as a method of theoretical integration to look at these differences as networks rather than subgroups.

### **Efforts via perceptions**

Perceptions are another element of complexity in the diversity-to-performance relationship. In their seminal work on teams as complex and dynamic systems, Arrow, McGrath and Berdahl note that diversity is not necessarily an objective and stable team property:

*“A common error in studying composition effects is to reify diversity as something that a group has in a fixed quantity based on the distribution of attributes among members. People tend not to express all aspects of self in a*

*given group or to be aware of all dimensions of other members...This is one reason why an exhaustive listing of attributes of people within a group does not fully define the membership composition. The composition and distribution of attributes perceived by group members will instead include some subset of this array, and which subset depends on what the group requires, what other members attend to, and what members' personal agendas are for their involvement."*

(Arrow, McGrath, & Berdahl, 2000, pp. 77–78)

In other words, the effects of team diversity may lean more on perceptions of difference as a mechanism rather than actual differences. This is embedded in a common definition of team diversity, summarized by van Knippenberg and Schippers as “differences between individuals on any attribute that may lead to the perception that another person is different from self” (van Knippenberg & Schippers, 2007, p. 517). While this definition clearly addresses perceptions, the common operationalization of diversity is objective categorical differences such as race, gender, or age. The steady overt nature of objective diversity makes it attractive to both scholars (for simple measurement) and managers (for straightforward guidelines regarding team composition) but may cloud the ability to understand the impact of diversity on performance.

Despite the tendency to ignore the role of perceptions in the diversity literature, there is a small but growing literature that looks at *perceived* diversity, defined by Shemla and colleagues as “the degree to which members are aware of one another’s differences, as reflected in their internal mental representations of the unit’s composition” (Shemla, Meyer, Greer, & Jehn, 2015). In their recent review of this emerging literature, Shemla and colleagues note three distinct relationships for these perceptions: self-to-team, subgroups within the team, and the team as a whole. Self-to-team perceptions refer to “the extent to which individual members perceive

themselves to be different from their unit” (Shemla et al., 2015, p. 5). This is frequently used in examination of relational demography (Tsui, Porter, & Egan, 2002), in which one’s differences relative to the larger team affect embeddedness and cooperation. Subgroup perceptions build on the growing literature regarding faultlines and investigate the “extent to which team members gauge their group to be split into subgroups” (Shemla et al., 2015, p. 5). In some ways, this represents a cognitive social structure approach, in which individuals are asked to describe how they understand their surroundings to be structured (Krackhardt, 1987). Finally, team diversity perceptions is a measure of perceived group heterogeneity, or “the extent to which members construe their group to be composed of individual who are different from each other on a certain attribute” (Shemla et al., 2015, p. 5).

### **Effects over time**

In their theoretical review of teams and time, Mathieu and colleagues identified three primary conceptualizations of time: (1) time as historical context, in which teams differ based on the era in which they exist; (2) time as a developmental marker, in which teams progress through a series of “phases” from formation to cessation; and (3) time as episodes, in which teams are conceptualized as moving through repeated performance cycles (Mathieu, Kuenberger, & D’Innocenzo, 2014). Each of these concepts of time should have a bearing on the impact of diversity on team processes and outcomes. This historical context of a team could impact the salience of particular dimensions of difference. Similarly, dimension salience may differ dependent on the team’s developmental phase. Finally, a preference for homogeneity may be a luxury of unhurried episodes in a team’s work cycle.

Despite these somewhat simple conjectures, teams scholars note a substantial lack of empirical work investigating time in teams generally, (Cronin, Weingart, & Todorova, 2011;

McGrath, 1997). Shemla and colleagues note that time is scarcely mentioned in the diversity literature, particularly in the realm of perceived diversity (Shemla et al., 2015). The malleability of perceptions is, as they note, an “essential difference between objective and perceived diversity” (Shemla et al., 2015). Most objective diversity measures do not change over time, or at least change very slowly. Perceptions, however, are far more malleable and transient. The way that these develop over time could dramatically reshape how intragroup differences impact the relational functioning of the team.

One notable and important exception to the absence of time in team diversity research is work by Harrison and colleagues (Harrison et al., 1998; Harrison, Price, Gavin, & Florey, 2002). Both studies examined the interplay of surface-level and deep-level diversity (observable and unobservable, respectively) and their relative impact on team outcomes (cohesion and performance) over time. These studies proposed and found that early diversity effects were associated with a lack of information on diverse team members, such that surface-level attributes were used to infer deeper-level characteristics about teammates.

As is common with other diversity research, the earlier work of Harrison and colleagues is focused on the collective level of analysis, using diversity measures that measured coefficients of variance (objective) or average perceived differences within the group (subjective). Although dyadic differences would presumably underlie both measures, they are not the focus of the analysis. As I will argue, this emphasis on the collective level of analysis could mask the structural microdynamics of differences at the dyadic level.

### **DYNAMIC INTRATEAM NETWORKS: THE EMERGENCE OF RELATIONSHIPS**

As demonstrated in this brief review, the study of team diversity is in many ways a well-worn road. As a field, our research on diverse teams spans several decades—yet we still struggle

with some of the basic questions. What kind of diversity matters? Are diverse teams always better? Why do some diverse teams excel, while others crash and burn? While the answers to these questions are far beyond the scope of this work, I suggest that part of the problem is an excessive focus on the team as the primary level of theory and analysis. (See Table 1 for a summary of the use of dyads or structure in the aforementioned theories of team diversity.)

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\*\*\* INSERT TABLE ONE ABOUT HERE \*\*\*  
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Consider the previous discussion of perceived diversity. One notable but missing relationship is that of dyads—what is the effect of perceived differences *between individuals* on a team? It could be assumed that some of the same effects would be seen, such as a preference to work with similar others, but the structure of these at the dyadic level might play a substantial role in determining the way that the collective works. In an assessment of the opportunities and threats in the existing diversity literature, Jackson, Joshi and Erhardt described a multi-level framework that considered entities both above and below the level of the group to understand the relationships between team diversity and outcomes (Jackson et al., 2003). While several research streams have tackled the effects of top-down contextual factors on diverse team outcomes (see Joshi & Roh, 2009 for a review), comparatively little work has been examined bottom-up effects, particularly those at the dyadic level (see Joshi, 2014; Joshi & Knight, 2015 for recent exceptions).

Dyads provides the unique opportunity to theorize on mechanisms that are below the team level while still being relational. The latter focus is particularly important when considering how interpersonal differences affect behavior. A classic definition of team diversity, as summarized in the review by van Knippenberg and Schippers, is the following: “differences *between individuals* that may lead to the perception that another person is different from self” (van Knippenberg & Schippers, 2007, p. 517; emphasis added). Our standard concepts of team diversity do not typically address the construct at this level of definition—this idea of inter-individual differences is more granular than our typical collective-level concepts of team diversity. In their review, Jackson and colleagues note that networks offer a unique and often underutilized perspective to the study of diversity in teams, since social and functional linkages can drive or be driven by differences between individuals (Jackson et al., 2003). Further, McPherson and Smith-Lovin (2001) note that the relationship between dyadic differences and overall network (or group) heterogeneity is not absolute, quoting a study by Marsden (1990) that found correlations ranging from .47 to .63 (Marsden, 1990; footnote 7). While interpretations of these correlation sizes may vary, it clearly indicates that there is substantial variance at the dyadic level that is not accounted for in team-level measures. Networks not only cover multiple levels of theory (i.e. collective, dyadic, and individual), but they also address the *structure* of relationships between and within these levels.

Regarding the role of time in team diversity’s effects, a network approach provides some advantages for handling questions of team microdynamics compared to aggregated models due to its more granular, interdependent and multilevel of concept of measurement. When time in teams is evaluated, the phenomenon is typically captured as a level change in a team state or attribute, but this change is almost always made up of smaller changes at lower levels. In other

words, team theories that are measured with aggregate measures are liable to miss nuanced changes at the lower levels, particularly if the constructs are like those mentioned earlier that are most meaningful at the dyadic level. Arrow and colleagues note that “group behavior involves *interactions* across at least three levels: constituent elements of groups, the group as an entity, and the contexts in which a group is embedded” (Arrow et al., 2000, p. 39; emphasis added). Importantly, these three layers are not independent, but instead they are part of an interactive system that cannot be studied in a piecemeal fashion. While the lack of longitudinal research in a network paradigm mirrors that in the aforementioned gap in the team literature, recent advances in network analysis are explicitly designed to evaluate network evolution (e.g. SAOMs).

Thus, in the next chapter, I will make a case for emergent networks as a new “effort” towards understanding diversity’s impact on processes and performance in teams. Viewing teams, and specifically diversity within teams, as an evolving network of dyadic relationships allows for theory on diversity that is simultaneously multilevel and structural—rather than our typical tendency towards teams theory that is purely collective in nature. Applying this view to the research questions discussed in the introduction, I will propose (1) that some structures of team diversity will encourage dyadic collaboration while others will hinder it, (2) that biased patterns of collaboration will persist in teams unless mitigated by these collaboration-encouraging structures, and (3) that while the tendency towards homogenous collaboration is stronger than that towards heterogeneous collaboration, it is the latter that will positively influence performance at the *team* level.

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## CHAPTER 1: PERSPECTIVES ON TEAM DIVERSITY

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## FIGURES AND TABLES

Table 1: Use of dyads or structure in other theories of team diversity

Theory	Representative articles	Dyads	Structure
Dimension typologies	Williams & O'Reilly 1998	None—although relational demography would come closest.	None
Categorization-elaboration model	van Knippenberg et al. 2004	None	None
Faultlines / Subgroups	Lau & Murnighan 1998; Carton & Cummings 2012	SGA uses dyads to determine likely subgroupings, but the dyad is not the level of analysis	Structure is discussed in terms of faultline or subgroup arrangement, but not at more granular levels
Methodological issues	Harrison and Klein 2007	None	Variety, separation and disparity are different forms of structure, but all at the team level
Perceptions of diversity	Shemla et al 2015	None—all perceptions reviewed by Shemla et al 2015 are the individual's perceptions of the team, not individuals	None.

**CHAPTER 2: TOWARD AN EMERGENT NETWORK THEORY OF TEAM  
DIVERSITY (UNDER REVIEW AT ACADEMY OF MANAGEMENT REVIEW)**

## CHAPTER 2: TOWARD AN EMERGENT NETWORK THEORY OF TEAM DIVERSITY

Teams are the *de facto* organizing mechanism for modern organizations, and these organizations are increasingly heterogeneous in terms of both demographic variables and knowledge, skills, and abilities (Mathieu, Tannenbaum, Donsbach, & Alliger, 2014a). Thus, the systematic study of diversity in teams is critically important. However, qualitative reviews (Joshi, Liao, & Roh, 2011; van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998) and meta-analyses (Horwitz & Horwitz, 2007; Joshi & Roh, 2009; van Dijk, van Engen, & van Knippenberg, 2012) reveal an inconclusive collection of results regarding the relationships between team diversity, team processes, and team performance. While some studies find that diversity in teams provides additional information and skills that can generate more optimal solutions to team tasks (e.g., Homan, van Knippenberg, van Kleef, & De Dreu, 2007), others find that diversity can generate conflict and stifle team cohesion (Harrison, Price, Gavin, & Florey, 2002a; Mohammed & Angell, 2004). These mixed results highlight “the bankruptcy of direct effects models” (van Knippenberg & Schippers, 2007: 518) and call for theoretical models that outline the complexity of effects stemming from diversity in teams.

Interestingly, team diversity is usually analyzed at the collective level (Harrison & Klein, 2007) but theoretically defined at the dyadic level (van Knippenberg & Schippers, 2007). For example, one common definition of team diversity<sup>1</sup> is “differences between individuals that may lead to the perception that another person is different from the self” (van Knippenberg & Schippers, 2007, p. 517). We suggest that this fundamental mismatch of levels between theory and empirical research can be addressed through concepts from a growing body of research on

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<sup>1</sup> Another classic definition of team diversity (Williams & O'Reilly, 1998) defines it as salient *interpersonal similarities or differences* (emphasis added).

## CHAPTER 2: TOWARD AN EMERGENT NETWORK THEORY OF TEAM DIVERSITY

team microdynamics (Arrow, McGrath, & Berdahl, 2000; Humphrey & Aime, 2014), which examines the development of dyadic and individual processes over time and their effects on team outcomes (Aime, Humphrey, DeRue, & Paul, 2014; Joshi, 2014; Joshi & Knight, 2015; Srikanth, Harvey, & Peterson, 2016; van Dijk, Meyer, Engen, & Loyd, 2016).

The microdynamics approach integrates two concepts that may help explain the mixed findings in the team diversity literature. First, while teams can be usefully interpreted as collective entities, they are also composed of interdependent pairwise relationships (Bavelas, 1950; Gittell, 2011; Joshi & Knight, 2015). If the mechanisms of team diversity operate primarily at this dyadic and relational level, then conceptualizing diversity as a team-level construct may miss important effects. Second, while teams often have stable characteristics, they also display states that emerge over time (Arrow et al., 2000; Cronin, Weingart, & Todorova, 2011; Mathieu, Maynard, Rapp, & Gilson, 2008; Mathieu, Tannenbaum, et al., 2014a; Waller, Okhuysen, & Saghafian, 2016). If diversity in a team influences its emergent states, then a model of its effects must be dynamic by design. A microdynamics perspective on diversity in teams is well situated to reveal nuances and insights that remain hidden in static or collective approaches.

A network perspective represents a particular form of microdynamics (Humphrey & Aime, 2014) that is uniquely suited to address the effects of diversity in teams. First, it is fundamentally relational while also recognizing the theoretical importance of the collective. This addresses the cross-level nature of team diversity, in which interpersonal differences influence both local (dyadic) and global (team) outcomes. Second, a networks perspective—particularly a dynamic one—provides a theoretical foundation for explaining how perceptions of diversity emerge over time. Network concepts such as diffusion and peer influence are useful tools for explaining how attitudes and behaviors in one part of the team can become shared with other

## CHAPTER 2: TOWARD AN EMERGENT NETWORK THEORY OF TEAM DIVERSITY

parts of the team over time. Finally, networks are not only relational but also structural, allowing theorizing on causal relationships that exist between the dyadic and team levels. For example, how do behaviors between two team members affect a third member who is observing? Network microstructures, or compound relations (Wasserman & Faust, 1994), provide a useful theoretical framework for addressing such questions.

In this paper, we build on existing work integrating psychological and network perspectives (Casciaro et al., 2015; Crawford & LePine, 2013) to generate a network-based theory that delineates the microdynamics of team diversity. We begin by addressing foundational assumptions in our theory: the network view of teams, the role of time in teams, dynamics of diversity perceptions, and the collaborative processes that underpin team performance. We then examine the various components of our model in turn: perceptions of similarity and difference between team members, their pairwise collaboration preferences and activities, and the ensuing network structures that these create. Finally, we discuss the implications of our model for team outcomes, both in terms of time and performance. Together, this emergent network model depicts a cyclical system of interpersonal differences, perceptions, and behaviors that should help untangle the implications of diversity for team functioning and performance.

### CONCEPTUAL FOUNDATIONS

#### **Teams as networks of relationships**

Recently, management scholars have called for a better integration of network and psychology perspectives in organizational research (Casciaro et al., 2015), which is particularly relevant in the area of teams (Katz, Lazer, Arrow, & Contractor, 2004; Murase, Doty, Wax, DeChurch, & Contractor, 2012). A network perspective is a useful lens into the functioning of teams due to its ability to simultaneously model (a) multiple levels of analysis, and (b) the

## CHAPTER 2: TOWARD AN EMERGENT NETWORK THEORY OF TEAM DIVERSITY

structure or architecture of relationships that exists in-between the classic levels of the individual and the group. Networks work at three fundamental levels: the actors or nodes, their dyadic relationships or ties, and the overall network (Borgatti & Foster, 2003). These three levels have been applied across a broad spectrum of organizational research, from the individual as a network in the case of intrapersonal identity networks (Ramarajan, 2014) to the level of institutional fields as networks (DiMaggio & Powell, 1983). Following other teams scholars, however, we examine the network at the team level, with its individual members at the node or actor level and their collaboration with one another at the tie or dyadic level (Mäs, Flache, Takács, & Jehn, 2012; Tröster, Mehra, & van Knippenberg, 2014).

This inclusion of the dyadic level is particularly useful for the study of diversity in teams due to the definitional conflict raised earlier. Team research traditionally takes an individual or collective approach to constructs, but the relational and interpersonal nature of team diversity would indicate that the most appropriate level of analysis rests with the dyad. While several research streams have tackled the effects of top-down factors on diverse team outcomes (see Joshi & Roh, 2009 for a review) and the bottom-up effects of team composition (Bell, Villado, Lukasik, Belau, & Briggs, 2011), far less work has examined intermediate effects, particularly those at the dyadic level. Since dyadic relationships are the basic building block of networks, a network approach to team diversity enables researchers to move closer to the true level of the phenomenon.

The network architecture of these dyadic relationships, which is a function of nodes and the structure of their ties (Ahuja, Soda, & Zaheer, 2012), can be used to predict behavior in teams. This reflects a compilation or configurational approach to team diversity, rather than the traditional compositional approach (Harrison & Klein, 2007; Kozlowski & Klein, 2000). Thus, a

network theory of teams allows for multiple conceptualizations of “we.” The classic team literature examines at least one way, defining the collective as the primary level of interest beyond the individual. However, a network perspective allows for a more nuanced view of “we”—which can include dyads, triads, cliques or other microstructures of dyadic relationships in addition to the collective (Espinosa & Clark, 2014). A network approach to teams and diversity incorporates work on structures such as faultlines (Lau & Murnighan, 1998; Thatcher & Patel, 2011) and subgroups (Carton & Cummings, 2012, 2013), but also considers alternative configurations of heterogeneity within teams and how those will impact individual, dyadic and team processes.

### **Time and diversity in teams**

Current theory recognizes teams as complex and dynamic systems (Arrow et al., 2000). While earlier work placed more focus on the inputs, processes and outputs (IPO; Hackman, 1987) of a singular team event, more recent efforts have extended the IPO framework to consider how repeated activities affect teams and their members (Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Mathieu, Kuenberger, & D’Innocenzo, 2014). Two prominent methods of conceptualizing time in teams research are developmental growth patterns and performance episodes (Ancona, Okhuysen, & Perlow, 2001; Mathieu, Tannenbaum, Donsbach, & Alliger, 2014b). The former views time as a series of phases or stages through which a team progress over its lifecycle (Gersick & Hackman, 1990; Tuckman & Jensen, 1977), while the latter models time as a series of performance engagements (Marks, Mathieu, & Zaccaro, 2001). Although these two streams developed relatively independently, recent work integrates the two to consider (a) how team states emerge from repeated engagements (effectively becoming markers of

developmental phases) and (b) how these emergent states affect future performance episodes (Mathieu, Tannenbaum, et al., 2014b; Waller et al., 2016).

The team diversity literature has historically taken a developmental view of time. For example, this approach has revealed differences in the influence of surface- and deep-level diversity over time (Harrison, Price, & Bell, 1998) and that these differences are possibly attributable to changes in perceptions of the team and social integration (Harrison et al., 2002). While this approach is clearly helpful in articulating when events related to diversity in teams may occur, we argue that it is only a partial picture of the role that time plays in these relationships. Integrating an episodic approach with the developmental one allows the investigation of emergent states which may be generated through a *cycle* of perceptions and interaction. These emergent states may predict the occurrence and timing of changes better than a strict developmental phase, because the occurrence of a focal event is related to the preceding chain of events (which lead to emergent states) rather than the simple progression of clock time (the developmental approach).

### **Perceptions of difference**

Historically, the teams literature has tended to view diversity as an objective construct, empirically if not always theoretically (Shemla, Meyer, Greer, & Jehn, 2015). While this is useful for the purposes of measurement and analysis, it makes the conceptual assumption that all differences are salient to all team members at all times. Depending on task demands, external forces, or internal dynamics, different attributes of diversity are relevant to different team members at different times (Arrow et al., 2000). Further, some dimensions of diversity (such as race) are based on social constructions (Ho, Roberts, & Gelman, 2015; Ho, Sidanius, Levin, & Banaji, 2011; Richeson & Sommers, 2016). While this does not necessarily diminish their impact

on human behavior, it does call into question their objective nature. Thus, diversity—or at least its mechanisms—is rooted in perceptions. Perceived diversity is “the degree to which members are aware of one another’s differences, as reflected in their internal mental representations of the unit’s composition” (Shemla et al., 2015: 91).

One of the core assumptions of our model is that these perceptions shift over time due to changes in the perceiver, the target, or the context. If diversity is viewed from the classic perspective as an objective property of a team, then it is likely to be stable over time. On the other hand, if team diversity is fundamentally a perceived construct, then its relationship to other constructs is much more likely to display temporal variance. We conceptualize diversity from a dynamic perspective in which teams move through repeated performance cycles (Mathieu, Kukenberger, et al., 2014). Taking this view allows for an emergent theory that includes reciprocal causality, with perceptions of difference and collaboration behaviors mutually influencing each other over time.

Considering diversity as a perceived phenomenon highlights an important qualifier for our model of team diversity and performance. In our theorizing, we do not make propositions regarding specific diversity dimensions (e.g. gender, job function) or categories (e.g., surface- or deep-level differences). In the interest of generalizability and context-free theory, we do not describe the role of specific dimensions, although we do recognize that certain dimensions will play important roles in various contexts.

### **The interplay of team diversity and team process in determining performance**

Collaboration is the engagement in joint activities towards a shared goal (Bedwell et al., 2012), and is assumed to be necessary to organizational functioning (Barnard, 1938). Scholars have recognized the importance of process optimization in determining team performance

(Srikanth et al., 2016; Steiner, 1972). Particularly in situations of substantial task interdependence (Thompson, 1967; van de Ven, Delbecq, & Koenig, 1976), collaboration behaviors should be highly predictive of team performance (Guimerà, Uzzi, Spiro, & Amaral, 2005; Uzzi & Spiro, 2005). While the connection between team process and performance is not a new idea, it is more common in the study of team diversity to look at performance as a linear function of *composition* rather than of *process*. We argue, however, that the equivocal results in the literature are due at least in part to this focus on direct effects from team composition rather than process.

The connection between composition, process, and performance highlights another important boundary condition for our model. Our model is primarily one of teams that are working with high task interdependence. To the degree that interdependence becomes simpler (i.e., more pooled or independent in nature), then the emphasis on collaborative process is reduced as the performance gain from complementary skills is reduced. Considering this from the perspective of task types (McGrath, 1984), our model covers primarily team activities related to cooperative processes such as idea generation or interdependent task performance rather than competitive ones such as resolving conflicts of viewpoint or power.

Going forward, we outline the fundamental building blocks of our process model: dyadic perceptions, collaboration behaviors, and the emergence of collaboration network microstructures. This cyclical and iterative process (depicted graphically in Figure 1) will then be used to describe how and when team diversity impacts team performance. After we consider each of these components in turn, we end by discussing their integration with existing theories of team diversity.

Insert Figure 1 about here

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## **DYADIC BUILDING BLOCKS: DIFFERENCES AND COLLABORATION**

### **Social identity cues**

To begin, we argue that the distribution and structure of diversity in teams creates salient identity cues that in turn drive dyadic collaboration. Diversity distribution refers to the spread of differences in a work team on an attribute (e.g., ethnicity, gender, job function; Harrison & Klein, 2007). Distribution is a compositional characteristic of team diversity, in that it represents the proportion of team members who possess a particular attribute (Blau, 1977). Diversity structure refers to the social architecture of team diversity on an attribute. Structure is a configural characteristic of team diversity, in that it describes emergent properties of diversity, such as faultlines (Lau & Murnighan, 1998; Thatcher & Patel, 2011). Together, these two characteristics of team diversity serve as exogenous factors affecting the dyadic collaboration process.

According to social identity and self-categorization theories (Tajfel & Turner, 1979; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987), people scan their social environments for indications of where they fit. They classify others as being part of their in-groups or out-groups depending on whether they appear to share important characteristics of their own identities. Importantly, these theories also suggest that people have multiple aspects of their identities that become salient in different situations (Johnson et al., 2006; Meyer, Shemla, & Schermuly, 2011); one's ethnic identity may be most salient in some situations, while one's job function identity may be most salient in others. Moreover, people often want the important aspects of their identities to be understood by their teammates (Thatcher & Greer, 2008). We adopt the notion of *social identity*

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*cues* (Guegan et al., 2017) to describe the process by which team members' various social identities become salient to others. Social identity cues are symbols of group membership. They include demographic identities such as indications of gender or ethnicity, as well as adopted identities such as indications of organizational membership or sports team affiliation. These cues act as external influences affecting the salience of a particular identity, working in conjunction with internal motivations such as self-esteem enhancement (Chattopadhyay, Tluchowska, & George, 2004) and uncertainty reduction (Chattopadhyay, George, & Ng, 2011)

Team diversity distribution and structure help determine the social identity cues that team members use to clarify their social environment. For example, consider a cross-functional project team made up of five members. Abhishek, Rahul, and Mahesh are all men of Indian ethnicity, and Elsa and Klara are women of Swedish ethnicity. They are all at the same hierarchical level in the organization and work in the same location, but all represent different job functions. Given this distribution and structure of team diversity, the most salient social identity cues are likely to be gender and ethnicity. Moreover, because these cues stack on each other, this group is likely to develop a faultline between the Indian men and the Swedish women. In a different configuration, other social identity cues may be more salient. For example, if Abhishek and Elsa were both senior executives while the others were at lower levels, then hierarchical position may be the most salient social identity cue in the team, rather than gender or ethnicity.

We theorize that social identity cues have two functional forms: affective cues and instrumental cues. *Affective cues* provide indications that team members share a social identity with each other. These cues are thus indications of the potential affective value in collaborating with another team member, as interacting with similar others often provides positive affect (Casciaro & Lobo, 2015). In the example above, gender and ethnicity are affective cues that

provide indications that it would be more pleasant to collaborate on one side of the faultline rather than across the faultline. In contrast, *instrumental cues* provide indications that team members are different from one another in terms of the resources they hold. These cues are thus indications of instrumental value in collaborating with another team member, in that one may perceive that another team member possesses resources that would help in accomplishing one's task (Casciaro & Lobo, 2015). In the example above, job function is an instrumental cue that provides an indication that a team member may need the expertise of a teammate to accomplish their task.

Later, we return to this idea by suggesting that the salience of particular social identity cues in teams shifts over time. We discuss how shifting social identity cue salience can explain the changing effects of surface- and deep-level diversity found in existing research (Harrison et al., 1998, 2002). This adaptability of cues is important in explaining how collaboration patterns emerge in teams. For now, we offer the following proposition:

*Proposition 1: The distribution and structure of team diversity provide both affective and instrumental social identity cues that team members use to make sense of their team's social environment.*

### **Identity convergence and complementarity**

Both affective and instrumental social identity cues serve as motivators of collaborative activity, and they operate through two different mechanisms. First, social identity cues can signal possible affective value through *identity convergence* between a focal team member (ego) and a

possible partner (alter)<sup>2</sup>. This occurs when identity cues in the environment, either from the distribution and structure of dyadic differences in the team or from subsequent collaboration patterns, lead the ego to perceive that the ego and the alter are similar on some important characteristic. This perception is likely what undergirds the frequently observed behavioral phenomenon of homophily in social networks. Consistent with similarity-attraction theory (Byrne, 1971, 1997), homophily is the common tendency for people to choose to associate with similar others (McPherson, Smith-Lovin, & Cook, 2001). Thus, homophily represents a social preference for homogeneity over heterogeneity in dyadic relationships. McPherson and colleagues (2001: 429) note that the phenomenon is such a well-established predictor of behavior between individuals across many types of behavior and dimensions of similarity that “homophily characterizes network systems, and homogeneity characterizes personal networks.”

Second, identity cues can signal *identity complementarity* by demonstrating useful differences between an ego and an alter, particularly in terms of task-relevant knowledge, skills, or resources. This suggests that *heterophily*—a tendency for dissimilar actors to form a tie, the exact opposite of homophily—can also predict interaction between individuals, particularly when the primary motive for a relationship is instrumental in nature (Rivera, Soderstrom, & Uzzi, 2010). Unlike homophily’s traditional focus on social ties, heterophily is more often used to predict task-related ties in teams with high interdependence, such as those found in academia and the arts (Rivera et al., 2010). Heterophily is also found in research on relational demography, particularly when differences between individuals are related to power or status (Chattopadhyay

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<sup>2</sup> Going forward, we will typically use the standard convention in the network literature by referring to the sender of a network tie (in this case, a collaboration preference) as the “ego” and the recipient as the “alter” (Casciaro & Lobo, 2015; Wasserman & Faust, 1994).

et al., 2004).

Together, affective and instrumental social identity cues provide a sense of the overall expected utility of collaborating with specific team members. When a team member (ego) perceives that another team member's (alter) affective cues suggest they are similar (identity convergence), they perceive an affective benefit of collaborating with each other. On the other hand, the ego may perceive affective cues that point to a lack of identity convergence, which may lead to a negative perception of affective benefit from collaborating with the alter. Similarly, the ego may perceive that an alter's instrumental cues signal that they have complementary knowledge, skills, or abilities (identity complementarity), which would lead them to perceive an instrumental benefit of collaborating with each other. Or they may perceive a lack of identity complementarity, which may lead to a negative perception of instrumental benefit from collaborating.

We suggest that people undertake a cognitive calculus (either consciously or subconsciously) of their expected utility from collaborating with other team members on the basis of these two mechanisms. In other words, they add up the perceived affective and instrumental benefits of collaborating with other team members; if the calculation is positive, they naturally collaborate; if not, they resist collaboration. This utility is similar to the idea that tie strength can be gauged from demographic similarity (Reagans, 2005), but expands it beyond demographic differences and considers the possibility that these differences vary in salience across time. Consider the international cross-functional team described earlier. As long as gender or ethnicity is the most salient social identity cue, collaboration will happen mostly within those demographic subgroups and not between them. Imagine that Klara is considering whether to collaborate with Elsa or Mahesh. She sees that Elsa's social identity cues (female, Swedish)

signal identity convergence with herself, but Mahesh's cues signal lack of convergence. Klara thus perceives a positive utility in forming a dyadic collaboration with Elsa, and a negative utility in collaborating with Mahesh.

But now imagine that Klara and Elsa are both designers, and Mahesh is an engineer. If job function is a salient social identity cue, Klara may perceive a positive instrumental utility in collaborating with Mahesh through identity complementarity, to the extent that Mahesh's different knowledge and skills would be useful to Klara in completing her team tasks. On the other hand, she may perceive a lack of identity complementarity with Elsa, signaling a negative instrumental benefit in collaborating with her. We propose that Klara, in a sense, will sum up the affective and instrumental utility of collaborating with Mahesh and Elsa, and that this utility depends on the social identity cues that are most salient to her.

*Proposition 2: In diverse teams, the likelihood of an ego's collaboration with a potential alter is increased by affective or instrumental identity cues that signal identity convergence and/or identity complementarity, which suggest increased collaboration utility with the alter.*

### **Collaboration mandates**

While perceptions of collaboration utility (derived from salient identity cues) should correlate positively with collaboration activity, team members do not always have full agency in selecting their partners. Organizational assignment to cross-functional teams, hiring mandates which increase minority representation in organizations, or leadership efforts to decrease internal silos can all constrain or encourage collaboration. We refer to such activities as *collaboration mandates*. Collaboration mandates will tend to override the cognitive calculus of utility described above. Thus, collaboration behaviors could be decoupled from identity cues and

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perceived collaboration utility if mandates are not aligned with team member interests.

While these mandates likely have a direct effect on collaboration activity, the interactive effect of mandates with team diversity is of greater importance for our model. When collaboration mandates align with a team member's perceived collaboration utility due to the team's diversity (e.g., a member is assigned by his or her supervisor to collaborate with someone that he or she perceives as similar and/or complementary), then mandates amplify the team member's interest in collaborating. However, when collaboration mandates work in opposition to collaboration preferences—inhibiting connections of perceived high value (identity convergence and/or complementarity) and promoting those of perceived low value (lack of convergence and/or complementarity)—then their influence serves to counteract the initial preferences of the team member.

For example, consider our example of the international cross-functional team. If gender and ethnicity remain as the only salient social identity cues, collaboration ties stay compartmentalized within their demographic subgroups. However, if the team's leader requires that Abhishek and Elsa collaborate on an ongoing task, an opportunity is created for a change in social identity cues. Abhishek may realize that Elsa shares an identity with him as a fan of the local soccer team, whereas Elsa may realize that Abhishek's background in communications will be helpful in explaining the technical details behind their project. While this partnership was unlikely to occur based on the straight prediction of team diversity distribution and structure, the external mandate caused it to happen.

Although collaboration mandates may initially appear to be a minor technicality, they help explain instances in which collaboration does not follow clear homophily patterns while also providing a rationale for suggesting ways to escape the homophilic path dependencies seen

in organizational networks. Thus, organizational factors represent an important exogenous microfoundation (Ahuja et al., 2012) to the emergent collaboration system. Without a source of external leverage, the network would be a closed system that would only be influenced once (at team initiation).

*Proposition 3: The connection between identity cues and dyadic collaboration through identity convergence and complementarity can be overridden by collaboration mandates.*

### **NETWORK MICROSTRUCTURES: EMERGENCE AND INFLUENCE**

#### **The emergence of collaboration network microstructures**

Emergent team phenomena meet four primary conditions (Lichtenstein, 2014; Waller et al., 2016). First, they arise from lower level activities, which in team settings usually refers to the individual or dyadic level. Second, they have some degree of endurance over time. Third, they are not fully decomposable back to their lower level components (the whole is greater than the sum of its parts). Finally, emergent team phenomena have reciprocal influence onto the lower level entities from which they arose. We suggest that (a) the dyadic collaboration choices described above create emergent collaboration microstructures as the process of collaboration iterates over time, and (b) the generated microstructures motivate future collaboration choices between team members. This idea of dual and reciprocal influence is consistent with the concept of emergence and also aligns with theory on organizational network dynamics which notes that “structural changes at the whole-network [team] level and the microdynamics at the tie and nodal ego-network [team member and dyadic] levels coevolve in a complex, interdependent fashion” (Ahuja et al., 2012: 438).

Collaboration microstructures are unique structural arrangements, or “compound

relations” (Wasserman & Faust, 1994) that are generated within the network of pairwise (i.e., tie and nodal level) collaboration choices. These particular patterns are important because they represent something beyond a simple aggregation of dyadic collaboration ties. In other words, the meaning of the specified arrangements of dyadic ties, when viewed at the team level, would be hidden when only viewing the sum of dyadic ties—it is their particular structure that matters. Further, the absence of a tie becomes as important as the presence of a tie, as both contribute meaningfully to the architecture of the team.

We suggest that these collaboration microstructures emerge over time, reflecting gradual changes in the microfoundations of the collaboration network. Ahuja and colleagues<sup>3</sup> (2012: 438) define network microfoundations as “the basic factors that drive or shape the formation, persistence, dissolution and content of ties” in a network, and they suggest four distinct categories for these factors. *Agency* represents a network member’s interest and ability to select ties within a given network. *Opportunity* encompasses the structural tendency to relate to people close to one’s self in the network. *Inertia* includes structural pressures to maintain or change network ties. *Exogenous* factors represent those that influence tie existence from outside the network itself (i.e. neither the actors nor the structure).

We will detail these microstructures of interest—reciprocity, peer influence, and triadic closure—in the next section, but we preview them here to connect them to this microfoundation framework. Each of these microstructures function primarily by altering the microfoundations of agency and opportunity. For agency, we suggest that microstructures influence an ego’s

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<sup>3</sup> We note that the framework provided by Ahuja et al. (2012) is primarily aimed at interorganizational networks, but both we and the authors of that framework argue that there is a relatively cohesive translation of these concepts to the interpersonal level of analysis.

perceived value of collaboration (affective and/or instrumental) with a particular alter, thus increasing the likelihood of enacting or maintaining a collaboration tie. For opportunity, microstructures also create a perceived social proximity (via social identity cues) between certain team members, affecting the likelihood that they would collaborate with each other.

Figure 2 shows the emergence of microstructures in teams that form dyadic collaborations across social identities (top) and within social identities (bottom). This figure represents networks of collaboration activity in diverse teams. Continuing our example of the international cross-functional team, if Klara chooses to collaborate with Elsa but not Mahesh, the team is likely to develop the microstructures at the bottom of Figure 2. Network ties will follow homophilic patterns, leading to faultlines separating strong subgroups. If she chooses to collaborate with Mahesh, however, the team is more likely to develop the microstructures at the top of the figure. Network ties will diffuse through both homophilic and heterophilic patterns, ultimately leading to collaboration across all team members. While we describe this path dependency in more detail in a following section, for now we make a fundamental proposition about the connection between dyadic collaboration and structure at higher levels.

*Proposition 4: As dyadic collaboration interactions accumulate over time, they form emergent microstructures of collaboration within diverse teams.*

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Insert Figure 2 about here

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### **The influence of microstructures on future cues**

As noted above, we expect that certain forms of emergent collaboration microstructures will in turn influence the social identity cues from which the process began. While these

microstructures differ in their specific forms, they share a common effect of establishing and normalizing a specific social heuristic of collaboration within the team by altering the microfoundations of agency and opportunity in the members of the team. When the microstructures display patterns that overlap with the basic assumptions of homophily—that people prefer to work with individuals who are perceived as similar for the affective value it is assumed to bring—then the microstructures have no novel effect and simply reinforce the common preference for homogeneity. However, when the microstructures work in opposition to homophily—that is, if they encourage collaboration ties with heterogeneous alters—then they add a new heuristic for establishing collaboration. This is consistent with the research finding that stereotypes tend to determine behavior (e.g., a given team member is or isn't a good candidate for collaborating) until disconfirming information is received (Fiske & Neuberg, 1990; van Dijk et al., 2016). Given the non-novelty of microstructures when they overlap with homophily, our descriptions below focus on this second instance of microstructures which normalize or legitimate heterogeneous collaboration ties in teams.

**Reciprocity.** In network theory, reciprocity is the social expectation of symmetric ties between two actors (Kilduff & Brass, 2010). Generally speaking, the effect of reciprocating a tie goes beyond that of simply adding another tie to a network as it also reinforces a potentially temporary tie by communicating connectivity to the original tie sender (now the recipient of the reciprocation). The act of reciprocating a tie back to the original sender communicates mutual interest, rather than a simple one-time opportunistic collaboration on the part of the reciprocator.

For collaboration ties across heterogeneous partners, mutual interest communicated through reciprocity is of particular importance. The original tie represented some level of risk, either that of lower affective value due to personal differences or lower instrumental value due to

unknown complementarities of knowledge and skills. However, *reciprocating* that tie becomes less ambiguous and thus easier, as personal differences and resource alignment are already tested. Respectively, this indicates a convergence in perceived identity cues and/or an increased perception of complementarity of resources. Assuming that the initial collaboration was at least modestly successful, reciprocation should be likely given that the original tie sender has already proven to be a worthwhile partner. We note, however, that this likelihood may vary depending on the content of the heterogeneity, since disparity differences (e.g. power, status) may generate asymmetrical collaboration preferences such that a high-resource team member would be less likely to reciprocate with a low-resource partner.

Once again, consider our example of the international cross-functional project team. If Klara initiates a tie with Mahesh and he reciprocates that tie by willingly collaborating with her, this affects how they perceive each other's social identity cues in the future. Gender and ethnicity become less salient cues, which increases the expectation of identity convergence in their collaborations in the future. In other words, they see each other more as common team members, rather than people with different demographic characteristics. At the same time, job function becomes a more salient social identity cue, which increases the expectation of identity complementarity.

*Proposition 5: Reciprocation of collaboration ties between an ego and an alter, even in the presence of heterogeneity, is likely due to change in either (a) the perceived convergence of affective identity cues or (b) the perceived complementarity of instrumental identity cues in that dyadic relationship.*

**Peer influence.** Social cognitive theory (Bandura, 2001) suggests that people learn from their environment, often vicariously through others whom they consider to be role models or

peers. The network literature often views the effects of peer influence as occurring between two nodes that are formally connected to the network. However, in the close context of a team (relative to the often more dispersed context of larger organizational networks), social influence can occur even without formal network ties between peers. In this way, team members are looking to other members for social proof, a decision-making heuristic in which an individual examines the activities of others to inform his or her own actions (Rao, Greve, & Davis, 2001).

We specifically propose that team members learn from, and to some degree mimic, the collaboration activities of others. If initial collaboration linkages tend to occur between relatively homogeneous peers (i.e., following understood subgroups in the team), then subsequent actions by team members not involved in the initial collaboration will tend to follow the default homophily pathway (bottom path in Figure 2). However, if collaboration patterns in the team are more heterogeneous in nature, this creates a role modeling influence which triggers a different set of identity or resource cues which in turn opens up new collaboration possibilities for other team members (top path in Figure 2).

In our international cross-functional team, imagine that Abhishek observes that Klara and Mahesh have collaborated effectively, and thus have created a reciprocal tie. This serves as social proof to Abhishek that successful collaborations across these particular demographic differences are possible in their team. Abhishek may then also initiate a tie with Klara. In this way, peer influence (through social proof) serves as a mechanism that diffuses ties across differences throughout the team.

*Proposition 6: A collaboration tie between a relatively heterogeneous ego and alter increases the likelihood that similarly heterogeneous peers of the ego and the alter will subsequently collaborate due to change in either (a) the*

*perceived convergence of identity cues or (b) the perceived complementarity of resource cues for those peers.*

**Triadic closure.** A third microstructure is based on the concept of triadic closure in networks, in which a tie between an ego and an alter is predicted by their mutual relationship with another alter. This phenomenon stems from classic work on weak ties (Granovetter, 1973), in which strong ties between individuals are more likely to be associated with redundancies in shared characteristics and information, whereas weak ties produce more innovative and unexpected combinations of information. While Granovetter’s primary interest was that of information flows, we utilize this construct to describe the relational bonds that are created which “align and coordinate action, enabling groups of nodes to act as a single node, often with greater capabilities” (Borgatti & Halgin, 2011).

If the triad is fairly homogeneous in nature, then complete closure of the triad is likely simply through homophily and social proximity. Triadic closure in heterogeneous triads, however, generates a different effect. If an ego has already established a successful collaboration relationship with a heterogeneous alter, this may generate new identity or resource cues in the ego regarding other partners of this alter. The ego may perceive that these other partners are potentially suitable new collaborators due to the success of the original ego-alter interaction. If these new collaborators represent a heterogeneous collaboration for the ego, then triadic closure creates different collaboration opportunities that would be exhibited if homophily was the only heuristic at play.

In the example of our team, imagine that in addition to the reciprocated tie between Klara and Mahesh, Klara and Elsa also have a (homophilic) reciprocated tie. The strong network effect of triadic closure would then suggest that Elsa and Mahesh will also form a reciprocated tie, thus

closing the triad. Similarly, Klara may also form reciprocated ties with Abhishek and Rahul, assuming that they have existing ties with Mahesh. In this way, triadic closure creates a strong pressure for tie diffusion in teams with reciprocated ties across demographic differences.

*Proposition 7: A collaboration tie between (a) an ego and an alter, along with (b) that alter and another alter, increases the likelihood of a subsequent tie between the original ego and the second alter, closing the triad, due to change in either (a) the perceived convergence of identity cues or (b) the perceived complementarity of resource cues in that partnership.*

## **TEAM OUTCOMES OVER TIME: PATH DEPENDENCE AND PERFORMANCE**

### **The diffusion of collaboration patterns over time**

The previous section considered collaboration microstructures as isolated phenomena, but their impact on team processes and performance is relatively weak if they remain as static constructs that only occur once. Thus, we now more fully consider the ways that collaboration microstructures diffuse across team networks over time and affect path dependencies of dyadic activity over time. The network literature is replete with examples in which attitudes and behaviors spread across interconnected, but the reasons behind this spread are often confounded (Lewis, Gonzalez, & Kaufman, 2012). One of two mechanisms are typically proposed to explain the diffusion of attitudes and behaviors across actors over time: homophily and peer influence. The former predicts that this spread is passive in nature and due to shared attributes between actors, and thus shared preferences, perspectives, or utility functions (McPherson et al., 2001), while the latter takes a more agentic view of network actors, who actively influence the peers with which they are connected to share their behavior or attitude (Raffaelli & Glynn, 2014). Recent scholarship notes that the observed network changes used to justify either homophily or

peer influence are often confounded, such that either mechanism could reasonably align with the offered explanation (Aral, Muchnik, & Sundararajan, 2009; Shalizi & Thomas, 2011).

The recognition that these two diffusion mechanisms function independently is helpful when considering the spread of collaboration in diverse teams, because the degree of their correlation will be predictive of the kinds of ties that develop in teams. In teams where microstructures display homogeneous patterns, peer influence and homophily mechanisms will reinforce each other and create a strong influence towards a steady state of homogeneous collaboration. This predicts classic demographic subgroupings (Carton & Cummings, 2012, 2013) and faultlines in teams (Lau & Murnighan, 1998). However, in teams where the correlation between homophily and peer influence patterns is weaker (in other words, when the ties encouraged by peer influence are nonredundant with those encouraged by homophily), collaboration ties are more likely to reach across heterogeneous gaps in the team (Ren, Gray, & Harrison, 2014). Figure 2 demonstrates two extreme examples of how this could present in a team, with Example 1 showing a steady state of full collaboration and Example 2 showing a steady state of homophily. In other words, the network effects of reciprocation, peer influence, and triadic closure create pressure for teams to move to one of the steady states in Figure 2.

*Proposition 8: Over time, the reinforcing patterns of network microstructures such as reciprocity, social proof, and triadic closure will cause a team to trend towards either a steady state of full collaboration or a steady state of homophily collaboration.*

The prior proposition suggests that a steady state will be strongly resistant to change. This is consistent with a strong structural view of networks, which views actor behavior as determined by the larger social context (DiMaggio & Powell, 1983; Meyer & Rowan, 1977).

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This is in tension with an agent-based view of networks, which views actor behavior as the determinant of networks rather than the inverse (Gulati & Gargiulo, 1999; Nebus, 2006). In the midst of this debate of causality, some scholars advocate a more nuanced approach, in which agency is somewhat constrained, but not ultimately determined, by structural features (Granovetter, 1985; Gulati & Srivastava, 2014; Rosenkopf & Padula, 2008).

This final position combines seemingly paradoxical views of structure and agency and holds that causation is reciprocal; this view is in line with our model of emergent collaboration networks in diverse teams. While our conceptualization clearly recognizes the role that network structure plays in shaping the perceptions and behaviors of its participants, we also hold that team members retain the ability to act in dissonance with the surrounding environment. Further, teams maintain a linkage to exogenous causation to team processes through the mechanism of collaboration mandates (as noted earlier). Thus, consistent with an open systems approach (Arrow et al., 2000), we propose that identity and resource cues are influenced over time by both internal (structural) and external (mandated) forces.

For example, imagine that our international cross-functional team has not established the reciprocated heterophilous ties described in previous examples, but instead have only collaborated within their demographic subgroups. At one point, Klara overhears Rahul talking about his favorite soccer club, which also happens to be Klara's favorite. This changes their salient social identity cues for each other; rather than seeing each other in terms of demographic differences, they now perceive their identity convergence as supporters of the same club. This may now cause them to initiate a collaboration tie due to the increase in perceptions of affective value, which in turn could put the team on the path to more heterogeneous collaboration.

*Proposition 9: Steady states in the collaboration system of a team can be*

*disrupted by altering identity or resource cues in the team.*

### **Team performance**

As the final component of our model, we return to the initial question regarding team performance. If collaboration ties diffuse through shifting social identity cues and network microstructures, how does this affect team performance? We begin with a statement regarding the direct impact of a team's level of diversity on its performance. Long recognized in the team diversity literature is the tension between the increased skills and abilities that differences bring and the anticipated interpersonal issues that accompany them. Some scholars argue that increased team diversity adds more potential information, skills, and abilities to the team, while others argue that increased diversity heightens the interpersonal tension, either real or anticipated (van Knippenberg & Schippers, 2007). These are sometimes modeled in a dual-effects or compensatory models (Williams & O'Reilly, 1998), but recent scholars are pushing back on the realism of these models (Srikanth et al., 2016). Regardless of the model, there are usually upsides and downsides to team diversity that are in tension, and the net effect of these is often a null influence on team performance.

This null finding has led scholars to declare "the bankruptcy of direct effects models" (van Knippenberg & Schippers, 2007), with which we agree. That effect, however, is based on the statistical examination of central tendencies in team performance. In other words, empirical research in this vein tests whether team diversity predicts differences in average values of team performance. In contrast, we contend that differing levels of diversity in a team changes both the performance floor (potential minimum) and performance ceiling (potential maximum), thus having an effect on the *variance* (but not the mean) of team performance. Relatively homogeneous teams have a higher likelihood of functioning well on an interpersonal level, and

thus have a fairly high performance floor. These same teams, however, would also have a fairly low performance ceiling, as their individual skills and abilities would be rather supplementary rather than complementary. As diversity in teams grows, these performance floors and ceilings would lower and raise respectively. The risk of interpersonal conflict would increase (lowering the performance floor), while the combinatorial potential of individual skills and abilities would rise (raising the performance ceiling). This reflects the “high-risk, high-reward” reality of diversity in teams. Figure 3 graphically illustrates this proposition.

*Proposition 10: Increased diversity in teams will increase the variance of performance across teams, not the average of performance.*

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Insert Figure 3 about here

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By shifting attention to performance variance (rather than performance averages), we can similarly shift our questions regarding the relationship between team diversity and team performance. Instead of asking *if* team diversity affects performance, we can ask *how* team diversity affects performance by altering related processes. In other words, at a given level of team diversity, what separates the high-performing teams from the low-performing ones? Our fundamental thesis, built from the perspective of an emergent collaboration process, is not the mere *existence* of interpersonal differences, but rather how a team *utilizes* those differences through its collaboration processes (Reagans, 2012). Teams that exhibit higher levels of heterogeneous collaboration ties—relatively successful partnerships that connect seemingly diverse individuals—will outperform teams with lower levels of heterogeneous collaboration. At the network level this would be represented through decreased patterns of clustering into cliques

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(Ahuja et al., 2012), as the heterogeneous ties would inhibit the tendency towards homophily.

This increase in performance from heterogeneous collaboration should be consistent whether the salient interpersonal differences are task-related or not, although the logic for the two cases does differ. An increase in collaboration success across task-related differences (for example, job function or training differences) should increase the utilization of these skills across the team. This is precisely the theoretical argument that the information processing rationale would make about the diversity-performance relationship (Reagans, 2012), although we hold that it only pertains to teams that “unlock” this potential by partnering across differences. For differences unrelated to the task (for example, demographic differences in many settings), successful collaborating across differences represents a non-constrained form of interaction. In other words, it is free from the interpersonal prejudice and preferential patterns that the social categorization approach to team diversity predicts, avoiding what some have called “coordination failures” (Srikanth et al., 2016).

In both cases (task-relevant differences or task-irrelevant differences), it is the *amount* of heterogeneous collaboration that occurs, rather than the ratio, that predicts performance. At first glance, this seems to argue (in parallel to the information processing perspective on team diversity) that teams with relatively high diversity should outperform teams with relatively low diversity—a statement that is not supported by the existing literature. However, this statement is conditional upon *successful collaboration* across the differences in the team. Combined with the earlier logic on team diversity and performance variance, we argue that this is the “high-reward” half of team diversity. It is equally possible that a highly diverse team will fail to collaborate effectively across differences (as the bottom path in Figure 2 indicates), making them worse off than a team that is less diverse and less high-risk. Thus, team diversity represents a necessary,

but not sufficient, condition for increased team performance.

Team interdependence is an important boundary condition for these statements on performance. Comprehensive or “team” interdependence tasks—in which group outcomes are the result of extensive interaction between teammates (van de Ven et al., 1976)—are the most likely to benefit from heterogeneous collaboration. This aligns with tasks that emphasize cooperation over competition (McGrath, 1984). Since the argument for heterogeneous collaboration is based on an optimized combination of complementary skills, this should only be seen to the degree that such optimization actually aids performance. For teams working on tasks with low interdependence, collaboration plays a less important role due to the reduced interaction inherent to the task.

*Proposition 11: Holding constant levels of diversity, teams with collaboration networks that span task-relevant dyadic differences will be associated with higher levels of team performance.*

*Proposition 12: Holding constant levels of diversity, teams with collaboration networks that span task-irrelevant differences will be associated with higher levels of team performance.*

### **DISCUSSION AND CONCLUSION**

Decades of research depict an unclear relationship between team diversity and its downstream outcomes, despite investigation of dimensional typologies, contextual effects, and measurement differences. Our position is that performance in diverse teams is determined not merely by its composition, but by the patterns of relating that members have with each other at a dyadic level. To this end, we articulated a theory of team diversity which models team performance on interdependent tasks as a function of the heterogeneity of ties in a team’s

emergent collaboration network. Diverse teams that have networks with more heterogeneous collaboration ties will reap the benefits of diversity (the application of unique skills and resources to the team's task), whereas teams with fewer heterogeneous ties will display the constraints of diversity (decreased cohesion and trust due to interpersonal differences). These networks of behavior are generated by perceptions based on social identity cues, which are initially based on fixed interpersonal differences, but are also adapted over time by the emergent microstructures in the collaboration networks themselves. Thus, collaboration networks in teams exhibit reciprocal causality with team member perceptions, which are affected by both interpersonal differences as well as interpersonal experiences.

### **Theoretical implications for teams research**

This paper contributes to work on teams, both broadly and specifically regarding diversity, in several ways. First, our model highlights the individual- and dyadic-level coordination mechanisms in the relationship between diversity and team-level outcomes (Reagans, 2012). While collaboration and coordination are recognized components of teamwork (Bedwell et al., 2012), we theorize about this at the dyadic level rather than the more commonly-considered team level. Additionally, we differentiate between kinds of collaboration, noting that heterogeneous collaboration ties are more beneficial to a team's performance than homogeneous ones. This extends recent models of coordination and team diversity (Srikanth et al., 2016) by more fully detailing the cycle of perception and collaboration that underlies team performance. We also specifically discuss ways in which team, dyad, and individual-level components mutually affect one another across levels. The process of emergence involves both an upward and a downward effect, which we describe through the mechanism of network microstructures. This complements other multilevel depictions of team diversity (Tasheva & Hillman, 2018) by

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extending the levels of analysis discussion over time.

Second, our model integrates episodic and developmental approaches to diversity's effects over time, viewing the passage of time as an iterative series of interactions that build upon one another. Time in teams has been theorized (Mathieu, Kukenberger, et al., 2014) as a set of historical periods, a sequence of developmental phases (Gersick & Hackman, 1990; McGrath, 1991; Tuckman & Jensen, 1977), or a cycle of performance episodes (Marks et al., 2001). Empirical literature on team diversity over time has typically favored the second approach (Harrison et al., 1998, 2002), aligning with the hypothesis that different dimensions of diversity will be relevant at different phases of team development. However, we contend that it is extremely difficult to generate a sequence of phases that is both generalizable enough to apply broadly yet specific enough to be meaningful. Further, a phased approach indicates a relatively closed system, which is essentially path dependent and resistant to influence from outside factors. By combining the notion of repeated episodes of interaction with the intuition from development models, we propose an open systems approach in which a team is theoretically capable of changing their collaboration patterns at any point given the proper adjustments to a particular episode. We believe this model is both (a) truer to the organizational reality in which management actively participates in improving team behaviors as well as (b) less fatalistic regarding the outcomes of diversity in teams.

Third, we have designed our model to be "dimension free", but not in ignorance of literature detailing the pervasive power of cultural stereotypes regarding demographic differences such as race and gender (Eagly & Chin, 2010; Ely, Padavic, & Thomas, 2012; Fiske, Cuddy, Glick, & Xu, 2002). Rather, our theory is designed to be applicable across a broad range of differences, with specific contexts determining the salience or relevance of a particular

dimension. Thus, we believe our theory works in tandem with research on the equity and inclusion aspects of diversity. We assume that prejudices from the broader context are found in the initial social identity cues that team members perceive from the composition and compilation of the team's differences, and that these would be updated based on subsequent collaboration episodes. This being said, it is likely that more persistent or deeply engrained stereotypes would be much more resistant to adaptation, creating a potential moderator for the relationship between emergent microstructures and downstream identity cues.

Fourth, we highlight the growing body of work on team diversity which evaluates the phenomenon through an examination of its underlying perceptual microprocesses. This complements recent theory on the microdynamics of diversity and stereotyping in teams (MIDST theory; van Dijk et al., 2016) that describes how these occur between team members and change over time. These stereotypes are categorized in terms of warmth and competence (Fiske et al., 2002) and have both positive and negative outcomes depending on the accuracy of the stereotype to the individual being perceived. Our network-based theory draws out the implications that stereotypes (as a subset of more general interpersonal perceptions) would have not only on dyadic collaboration tendencies, but also on emergent group-level properties such as network microstructures and team performance. Thus, by extending MIDST theory more explicitly across levels, we can describe the emergence process over multiple interaction cycles.

Finally, we also contribute to the broader teams literature by generating theory that describes the microdynamics of emergence in teams through the lens of intrateam networks. The strength of a network approach lies in its ability to explicate the dyadic mechanisms that underlie team-level theories of diversity in terms of the patterns that these dyads create. Arrow and colleagues (Arrow et al., 2000: 39; emphasis added) note that “group behavior

involves *interactions* across at least three levels: constituent elements of groups, the group as an entity, and the contexts in which a group is embedded.” Importantly, these three layers are not independent, but instead are part of an interactive system that cannot be studied in a static or piecemeal fashion. We contribute to defining this system by conceptualizing a way that perceptions and the microstructures of dyadic behaviors can mutually reinforce (or attenuate) the effects of team diversity on team performance.

### **Theoretical implications for related fields**

In addition to our primary contributions to the team literature, we also contribute to the larger social network and social identity literatures. First, we address the need to examine “the choices and balance of homophily and heterophily” (Rivera et al., 2010: 97) and determine how and when one takes precedent over the other. We argue that, while homophily is often the path of least resistance in team collaboration networks, local emergent microstructures can change team members’ calculations of affective and instrumental benefits. If these calculations shift properly, they enable a team member to utilize heterogeneous collaboration opportunities more fully.

Second, we also address questions in the homophily research regarding multidimensionality (or multiplexity, in network terms). Homophily is classically rooted in a focus on observable demographic characteristics, and therefore is understood to be static and unchanging over time. Additionally, these dimensions are assumed to exist in isolation from other (perhaps more) salient dimensions, which makes sense as a simplifying assumption but flies in the face of real-world applications of diversity in teams. Our model uses research on social identity to reflect a more perceptual and multi-faceted approach to interindividual differences that can enhance the homophily approach to team networks.

Third, we contribute to a growing interest in the co-evolution of agents and structure in

networks (McPherson et al., 2001). While a long-standing paradox in social science and network theory debates between agentic and structuralistic causation (Gulati & Srivastava, 2014), we argue that people both build collaboration networks and are subsequently affected by them. Thus, our model depicts people and relationships as mutually causal over time. We believe that this proposed reciprocal causation is aided by a dynamic focus on networks, whereas a static network perspective is unable to hold both effects in tension.

Finally, we contribute to the social identity literature by introducing the concept of affective and instrumental social identity cues in work teams. We suggest that team members use these cues to make sense of the social environment of their team, and as tools to decide with whom they would like to collaborate. When they perceive affective identity cues that signal identity convergence, this increases their calculation of the utility of collaborating with that team member. When they perceive instrumental identity cues that signal identity complementarity, this also increases their calculation of the utility of collaborating with that team member. When diverse teams first form, however, these cues tend to stand in opposition to each other. Homogeneous others provide positive affective value but negative (or null) instrumental value; heterogeneous others provide negative affective value but positive instrumental value. Over time, however, the social identity cues shift, such that teams with successful collaborations across differences can expect both positive affective value and positive instrumental value in future dyadic collaborations.

### **Empirical implications**

Our model also has implications for further empirical research on diverse teams. First, we suggest reconsidering the use of team diversity as an antecedent to performance. Meta-analyses and reviews suggest that these measures predict little variance in team performance, and our

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theoretical argument is that team behaviors are more proximal to performance than team composition. This is not to say that team diversity is irrelevant as an input to team performance, but rather that it becomes a necessary but not sufficient condition. Interpersonal difference must still exist in order for teams to utilize them, but they are not predictive of performance by themselves.

Second, our theory describes how variant interpersonal perceptions are over time, thus raising concerns with the use of objective measures of difference (Shemla et al., 2015). While objective differences have a clear advantage from a practical perspective, our theory suggests that their correspondence to perceptions of difference are unknown. If these perceptions are (a) closer in the causal chain to performance, but (b) only loosely correlated with objective differences, then using objective differences in empirical tests will result in very noisy causal relationships. Using perceived differences, on the other hand, is more likely to uncover true causal effects because it more accurately reflects the lived reality of teams.

Third, our model highlights the continued importance of measuring mediating mechanisms in understanding what drives team performance in the context of diversity. This is not a new observation (van Knippenberg & Schippers, 2007), but it is one that bears repeating. This is particularly true if we assume that these mediating mechanisms are emergent states that can build or weaken over time, as the mediating mechanism then itself becomes the causal agent in future cycles, rather than a simple static link between diversity and performance.

Finally, our model suggests the need for increased knowledge and proficiency with the use of network models—particularly dynamic network models. This is of heightened importance when network ties are the dependent variable (as in the case of interpersonal perceptions or collaboration behavior), as the assumptions of traditional regression models are violated due to

non-independence of the observed outcome. Several statistical models exist for predicting tie creation, including exponentiated random graph models (ERGMs; Goodreau, Kitts, & Morris, 2009; Kim, Howard, Cox Pahnke, & Boeker, 2016; Lusher, Koskinen, & Robins, 2012), stochastic actor-oriented models (SAOMs; Snijders, 1996; Snijders, van de Bunt, & Steglich, 2010) and latent space models (Hoff, Raftery, & Handcock, 2002; Sewell & Chen, 2015), but these have yet to see widespread adoption in the teams literature.

### **Practical implications**

**Team selection versus team process.** For organizational leaders, the questions about team diversity often involve the assignment of particular members to a team. This focus on composition implies that the primary work of management is done once at the beginning, and the outcomes of a team's diversity are mostly fixed. By adopting a relational and dynamic perspective, we suggest a more process-oriented approach that moves the emphasis away from the compositional questions. Instead, our theory focuses management effort on generating fruitful collaboration between heterogeneous individuals, particularly since those team members may not be likely to see the potential in each other due to the arrangement of identity cues. This does not suggest, however, that team composition is irrelevant. In fact, our concept of team diversity assumes some base level of difference in the team. For a team to reach the best results, it must not only have the right guidance in terms of making collaboration ties; it also needs to have a sufficient level of variety in knowledge, skills, and abilities to be able to benefit from those differences. Thus, we answer the original question of composition (i.e., create a diverse team) and shift the question to how one guides a team's collaborative process.

**Organizational factors.** In tandem with the emphasis on process over composition, we leverage concepts from open systems theory (Arrow et al., 2000; Scott & Davis, 2007) to

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highlight that the collaboration systems in teams are not closed entities. Rather, they remain open to local and global inputs from the context, whether that be organizational policies or leadership influence. Purposeful and authentic rearrangement of identity cues can generate powerful changes in teams. For example, two employees with complementary skillsets but a natural distrust of each other could be assigned to work together with a third “bridge” partner whose mandate is to help the partnership succeed. Alternatively, organizations can create incentive systems that reward the challenging work of assembling collaboration partnerships across differences.

The effect of diversity in teams on team processes and performance is a question of substantial theoretical and practical importance. However, the literature to date paints a relatively murky picture of these relationships. By proposing a network approach to team diversity, our fundamental argument is that a dyadic, structural, and dynamic approach is truer and closer to the phenomenon than static and aggregated team measures. In this paper, we offer one solution to this by outlining an emergent network perspective on diversity in teams. This approach recognizes the inherently relational nature of team diversity and refocuses the discussion on collaboration within these relationships rather than the composition of the group. In doing so, our intention is to stimulate new approaches to a persistent question.

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**FIGURE 1**  
**Conceptual model**

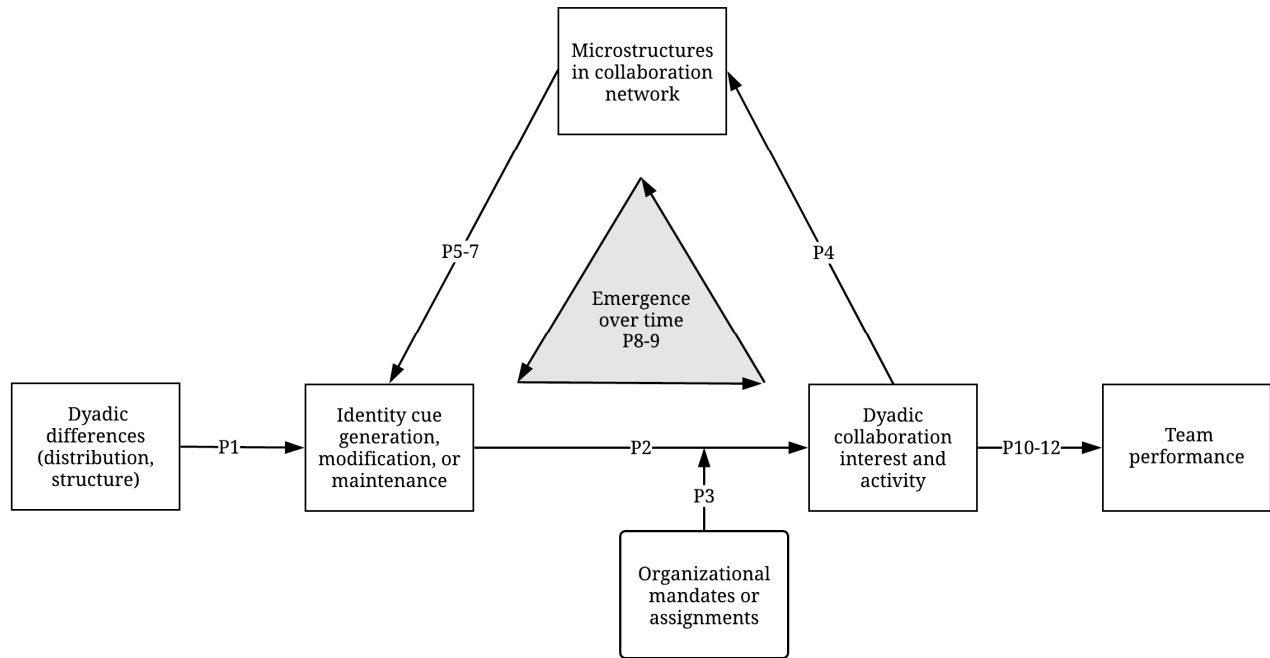
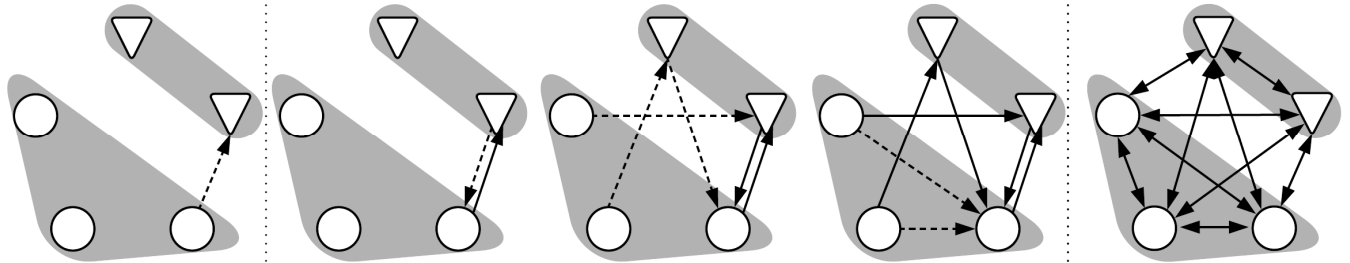


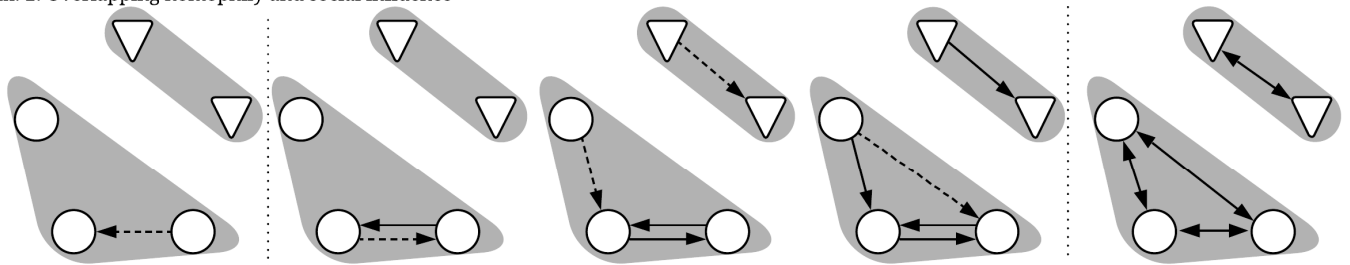
FIGURE 2

Examples of microstructures and diffusion pathways in team collaboration network

Ex. 1: Non-overlapping homophily and social influence



Ex. 2: Overlapping homophily and social influence

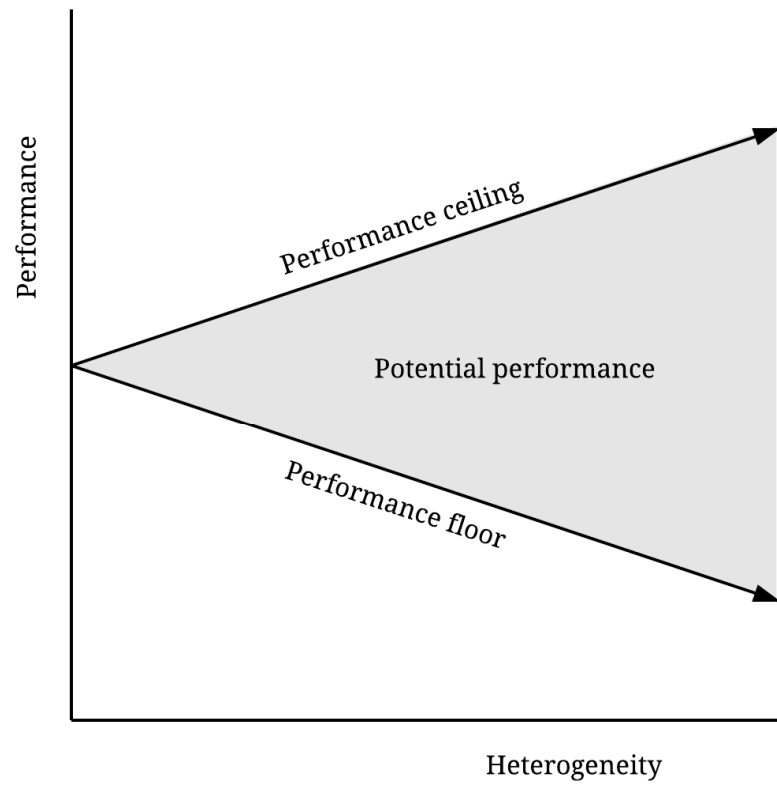


	Reciprocity	Peer influence	Triadic closure	
Initial step	Microstructures (emerging over time)			Steady state

Shapes represent commonly shared dimensions of difference (e.g. gender, ethnicity)  
 Shading represents default homophily preferences  
 Solid lines represent pre-existing collaboration ties  
 Dotted lines represent new collaboration ties

**FIGURE 3**

**Performance floor and ceiling relative to team diversity**



**CHAPTER 3: EMPIRICAL TESTS OF HETEROGENEOUS COLLABORATION AND  
TEAM PERFORMANCE**

## HYPOTHESES

In Chapter 2, I built a case for a concept of team diversity that is emergent and structural. While the bulk of prior team diversity research looks at the direct effect of team composition on team performance, my thesis is that the primary source of differentiation in team outcomes is the evolving patterns of perceptions, relationships and partnerships between members of the team. Thus, the ultimate measure of a theory of team diversity is in the actual outcomes of the group. In other words, how does this reconceptualization of diversity relate to performance, if at all? Given that the correlation between dyadic-level differences and team level heterogeneity is modest at best (Marsden, 1990), analysis at the dyadic level has the potential to yield insights that have not appeared at the collective level.

An initial hypothesis could be that increased collaboration in any form leads to increased performance, thus circumventing the impact of diversity in the team. However, I argued earlier in Chapter 2 that not all collaboration is equal. Instead, collaboration which occurs successfully across perceived differences in the team, whether these be related to the task or not, will be more valuable to team performance than is collaboration between more homogeneous individuals. Conversely, heterogeneous collaboration which is either not attempted or is unsuccessful will have a negative impact on the team's performance. This makes diversity in a team a high-risk, high-reward proposition. Teams that are willing to exert the effort to learn to utilize their differences have the opportunity to outperform more homogeneous groups, but teams that fail to capitalize on these non-redundancies would have been better off without them.

Considering both the upside potential and downside risk of team diversity in tandem helps to explain the null effects of team diversity on team diversity found in several reviews mentioned in Chapter 1. If the risk and reward distribution are somewhat evenly split between

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the upside potential of complementary fit and the downside potential of decreased social cohesion (or competence and affect respectively from the earlier discussion of collaboration), then the overall effect of average differences within the group should be mostly null or slightly negative due to a potentially weaker effect of heterophily compared homophily. However, the performance ceilings and floors of teams will move apart from another as team diversity increases. While a relatively homogeneous team would have a relatively high performance floor (“low risk”), it would also have a relatively low performance ceiling (“low reward”). As diversity in the team increases, the potential floor would move lower (“high risk”) and the potential ceiling would move higher (“high reward”). If this argument holds true, then changes in levels of team diversity affects *variance* in team performance, rather than *average* team performance.

*Hypothesis 1: Increased diversity in teams will increase the variance of performance across teams, not the average of performance.*

If team diversity affects the variance of team performance and not the average, what can teams do with their differences to put themselves closer to the ceiling of their potential rather than the floor? As I initially put forth in Chapter 2, I maintain that the potential in a diverse team is only realized if team members individually collaborate in a fashion which harnesses the benefits of heterogeneity. Consider two extreme (and admittedly unrealistic) cases—collaboration between completely homogeneous partners (“clones”) on the one hand and between completely heterogeneous partners (“opposites”) on the other. In the team of the “clones”, their extreme similarity could only generate collaboration between homogeneous partners, while the team of “opposites” would by definition collaborate with heterogeneous partners. The clone team would perhaps collaborate more easily, but each unit of collaboration

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would be worth less of a performance gain on tasks that benefit from the combination of unique knowledge, skills, or abilities. On the other hand, the opposites team could be much more reluctant to collaborate due to their obvious differences, but each unit of collaboration would be far more valuable than in the homogenous team due to the richer toolbox of unique skills and abilities that would be used on the task.

Extrapolating this logic to a more realistic intermediate level of team diversity, we can compare two general types of collaboration ties—those that happen between relatively heterogeneous partners and those that happen between relatively homogeneous partners. While the latter are perhaps more ubiquitous, the former play a stronger role in improving team performance when compared in a one-to-one manner. At a team network level, this would mean that teams which exhibit more heterogeneous collaboration patterns should outperform teams which exhibit homogeneous collaboration patterns. This statement assumes that levels of diversity are held constant, as differences between individuals in the team becomes a necessary, but not sufficient, condition for differences in team performance.

It is important to note that this effect should be substantial while still controlling for both overall levels of collaboration in the team as well as the degree of diversity that exists in the team's composition. While this serves a practical empirical purpose of comparing all teams on a level playing field, it also tackles two important and related theoretical questions. First, the performance impact of increased levels of *heterogeneous* collaboration is distinguished from increased levels of *overall* collaboration. This further strengthens and clarifies the argument that homogeneous and heterogeneous collaboration patterns have distinct effects on team performance. Second, it is tempting to ignore team diversity as an essential element in the causal chain of team performance as the theoretical focus shifts to the underlying microdynamics of

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collaboration. However, interindividual differences remain an necessary condition for heterogeneous collaboration to occur, even if team diversity is not sufficient by itself to reliably predict team performance. By controlling for levels of team diversity and collaboration in our models of heterogeneous collaboration and performance, I deal with these potential confusions and confounds empirically as well as theoretically.

*Hypothesis 2: Holding constant both levels of diversity and collaboration, teams with collaboration networks that span differences between individuals, whether they be (a) task-relevant or (b) task-irrelevant, will be associated with higher levels of team performance.*

### **METHODOLOGICAL OVERVIEW**

Testing these hypotheses poses several data constraints. First, the data must have a measure of collaboration at the dyadic level. Second, the data must be longitudinal or have multiple measurements over time. Third, the focal activity must contain a relatively high level of interdependence, given this is a boundary condition of the theory described in Chapter 2. Finally, the data need to describe multiple dimensions of diversity, with some being logically connected to the task and others being unrelated to the task.

Two data samples were obtained for testing, the first of undergraduate students and the second of professional basketball players. (See Table 1 for details on these samples.) Across both samples, the same analytical procedures are utilized to (a) evaluate the relationship between levels of diversity and variance in performance, (b) model the factors which predict collaboration tie formation at the dyadic/relational level, and (c) use coefficients generated in the prior step to predict performance at the team level.

Code samples for these analyses in this study are available in Appendices 2–3.

**STUDY 1: UNDERGRADUATE STUDENTS**

**Sample**

Business undergraduate students ( $N = 194$ ) were recruited to participate in as part of a class requirement in a core management course at a large university on the west coast of the United States. The average age of participants was 21.4 years, with 56% male, 58.2% white and 33.0% Asian. Participants were randomly assigned into 44 teams (mean team size: 4.41) for participation in an hour-long research session.

**Task and procedure**

The primary task utilized in this study was a team exercise commonly known as “Broken Squares” (Bavelas, 1973). While this game is frequently used by practitioners in team building scenarios to highlight the interdependencies of team tasks and the importance of collaboration, its origin is in the lab as a method to evaluate the collaborative processes of teams. The object of the game is to silently reassemble a set of squares from a collection of smaller shapes (see Appendix 1 for templates of the puzzles used). These smaller pieces are initially distributed to team members in such a way that no member has all the pieces needed to make a square within their own possession. Therefore, teammates must share pieces with each other to successfully complete the task. There are several constraints on communication that require interdependent thinking and behavior: (a) “No one can say anything or gesture in any way to communicate with fellow members”; (b) “No one can take or pull a piece from another member, unless s/he gives it to them”; (c) “You can give a piece to anyone you like”; and (d) “You cannot refuse any piece you are given.” These constraints help to clarify the activity of collaboration from its antecedents or consequences.

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This task was selected for several reasons. First, this task fits a fundamental boundary condition of this theory—complex interdependence. Unlike more linear processes such as factory work, my theory of collaboration is particularly centered on creative or problem-solving work, in which the “correct” answer is often unclear if it exists at all. Thus, full participation and engagement are key for teams to reach their full potential in terms of collaboration. This task reflects this emphasis, in that puzzle solution is literally impossible without at least minimal collaboration, and increased collaboration should substantially improve outcomes.

Second, the constraints on communication help isolate the *behavior* of collaboration (passing pieces) from *antecedents* or *consequences* of collaboration. While a holistic view of team collaboration requires multiple interlocking team processes (e.g. planning) and assumes similarly complex outcomes (e.g. team learning), the measurement of collaboration for the purposes of this study needs to separate the *action* of collaboration from its precursors and consequences. Recording the movement of pieces between team members provides an unobtrusive and objective measurement of collaboration.

Third, performance can be solely evaluated in terms of time, rather than being confounded with evaluations of decision quality. Although there are a variety of efficient passing patterns to complete the puzzles, there is only one correct answer. By holding the quality of the answer constant, performance can be succinctly reduced to time-to-completion.

Student teams played two rounds of this game: an initial training round and a subsequent follow-up round, between which an interlude allowed them to discuss and possibly generate teamwork strategies. Puzzles differed in content, but not in general strategy, between the two rounds. No planning was allowed prior to the first round. All analyses are performed on the

second round of the exercise to reduce noise in the data due to luck in the puzzle building process.

### Measures

**Periodicity.** While gameplay was captured in real-time by video and was coded as such, analysis requires an aggregation into time periods or “waves”. A wave interval of one minute was used in these analyses, with the intention of balancing granularity and tractability.

**Dyad-level dependent variable: Dyadic collaboration.** Dyadic collaboration was measured as the passing of game pieces from one player to another in the focal time period. For analytical purposes, this is evaluated as the binary presence or absence of passing between members rather than the count value. This is a common limitation of network analysis (reducing continuous data down to a binary value), but future analyses may relieve this constraint. The heterogeneity of this collaboration was evaluated with the following formula:

$$\sum_j x_{ij} I\{v_i \neq v_j\}$$

where the indicator function  $I\{v_i \neq v_j\}$  is 1 if satisfied and 0 if not (Ripley, Snijders, Boda, Voros, & Preciado, 2018).

**Team-level dependent variable: Team performance.** Team performance was measured as the amount of time required to complete the exercise. Thus, a lower time on the exercise (and in the analysis) represents a better performance for the team. If teams could not finish the exercise, then their performance was marked at the maximum time (fifteen minutes). While this represents a slight right-censoring of this variable, observations of the experiment indicate that very few teams solved the puzzle in the time just before the deadline, making the cutoff more akin to an adjustment to outliers.

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***Diversity dimensions.*** First, teams were randomly assigned to conditions that manipulated the distribution of strategy hints for solving the puzzle to simulate a form of information diversity, such as “The final solution has five squares” or “Passing pieces is required to solve this exercise.” This information represents a form of task-relevant diversity, allowing for the evaluation of Hypothesis 2A. In total, four information conditions were created: (1) “all”, in which all hints were given to all participants; (2) “variety”, in which each participant received one unique hint; (3) “separation”, in which two even subgroups were created which had the same hints internally but did not have the same hints as the other subgroup, and (4) “disparity”, in which one person received all of the hints and other players received no hints. The “all” and “variety” conditions are excluded from the informational diversity analysis since they (a) share a distributional pattern in common but vary in the number of hints given and (b) confound heterogeneous passing with passing in general, since every subgroup is made of one team member and thus any pass is a heterogeneous one by definition. The distribution of information was also signaled in the experimental setting through seating arrangements and nametag colors, following prior research (Homan, van Knippenberg, van Kleef, & de Dreu, 2007).

Second, gender and ethnicity are surface-level differences that, while apparent to even new acquaintances such as those in a behavioral laboratory, should be task-irrelevant for the purposes of this exercise. However, Hypothesis 2b suggests that even task-irrelevant differences can affect performance if they create suboptimal constraints on collaboration patterns in the team. To prevent suspicion regarding the hypotheses of the research, these demographic differences were measured by survey question and were not manipulated in the group assignment. Questions regarding ethnicity were asked in a multi-select fashion to reflect

multiethnicity in individuals. Thus, analyses were conducted regarding people who did or did not identify with the top two ethnic groups (white and Asian) in succession.

**Controls.** At the dyadic level, two network effects are included that are found frequently enough across all settings that they are default controls in this analytical procedure described later. First, outdegree density reflects the likelihood that an ego with a high total quantity of passes is more likely to send a collaboration tie to an alter than an ego with fewer total passes. This is measured using the following formula:

$$\sum_j x_{ij}$$

where  $x_{ij} = 1$  or  $0$  reflects the presence or absence respectively of a directed tie from  $i$  to  $j$  (Ripley et al., 2018).

Second, reciprocity reflects the likelihood that an ego will make a pass to an alter that passed to them in prior rounds. This is measured with the formula:

$$\sum_j x_{ij}x_{ji}$$

where  $x_{ij} = 1$  or  $0$  reflects the presence or absence respectively of a directed tie from  $i$  to  $j$  and  $x_{ji} = 1$  or  $0$  reflects the presence or absence respectively of a directed tie from  $j$  to  $i$  (Ripley et al., 2018).

At the team level, measures of compositional diversity are included in recognition of the logic that that network processes are a better predictor of performance than team composition. These are operationalized by including Blau's index for the dimensions in question in the team-level regressions. The coefficient of variation was also evaluated for information distribution, since this could potentially be considered a disparity dimension (Harrison & Klein, 2007). However, very few differences existed between models using the two indices, so Blau's index is

used in all models for consistency. Total number of passes was also used as a control variable to differentiate heterogeneous collaboration from total collaboration as a team performance predictor.

### **Analysis**

Hypothesis 1 was evaluated with a combination of (a) the studentized Breusch-Pagan test (Koenker, 1981) to statistically test for heteroscedasticity (variance in regression model residuals correlated with predictors in those models) and (b) visual inspection of the scatterplot relating diversity composition to team performance (see Figures 1–3) to determine if the shape of any heteroscedasticity matches the hypothesized pattern (performance variance increasing as heterogeneity increases).

Hypotheses 2a and 2b were tested with a two-stage approach that combines an initial analysis at the dyadic level using models that predict network ties with subsequent analysis at the team level using more traditional linear regression models. This two-stage procedure is essential, as it allows for the analysis of causation from lower-level entities (“bottom-up”). Traditional multilevel analyses typically struggle in testing this direction of causation (Preacher, Zhang, & Zyphur, 2011; Preacher, Zyphur, & Zhang, 2010), and similar two-stage approaches have been used in prior work with similar research questions (cf. Chen, 2005; Joshi & Knight, 2015; Knight, 2013).

For the first stage analysis, stochastic actor-oriented models (SAOMs; Snijders, van de Bunt, & Steglich, 2010) using the *RSiena* (version 1-2.9; Ripley et al., 2018) package in R (version 3.4.3; R Core Team, 2015) were used to evaluate the predictors of tie creation (that is, collaboration) between actors (players) in our networks (teams). SAOMs are part of a larger family of network models, which also includes exponentiated random graph models (ERGMs;

Goodreau, Kitts, & Morris, 2009; Kim, Howard, Cox Pahnke, & Boeker, 2016; Lusher, Koskinen, & Robins, 2012) and latent space models (Hoff, Raftery, & Handcock, 2002; Sewell & Chen, 2015), that allow for actor, dyadic, and structural predictors of individual- and dyad-level outcomes. Typical ordinary least-squares regression or mixed-effects models are not capable of this analysis due to (a) the non-independence of the data and (b) the use of structural components as predictors.

SAOMs were chosen for these analyses due to their inherent longitudinal approach, as well as their actor-oriented nature. Within the network literature, a well-recognized tension exists regarding the causal relationship between nodes and the network structure (Granovetter, 1973; Gulati & Srivastava, 2014). Some theories suggest that network structure strictly determines the actions of the nodes, whereas others suggest that the actions of the nodes determine the network structure. In other words, where does the network come from (Morris, 2002)? SAOMs assume the latter position, and thus networks reflect an emergent structure that is primarily shaped by the actions of the nodes. However, SAOMs also allow for structure to have a reciprocal downward effect on future behaviors by using network structures as predictors as well as outcomes.

The minimal data input for a SAOM is a dependent variable in the form of multi-wave network data, which is augmented in this analysis by a collection of node-level (person-level) covariates, some which are fixed over time and some which change over time. These network datasets are compiled by *RSiena* and used to simulate (via a continuous-time Markov chain) all of the *ministeps* involved in moving the network from one observation to the next. Each simulated ministep encompasses an individual tie's change from one state to another (e.g. non-existent to existent). These simulations (repeated many times over) generate probabilistic

estimates for various explanations (“effects”) of the underlying processes that generated the observed network data. It should be noted that, just like any other method of statistical inference (e.g. ordinary least squares regression), the results from a SAOM in isolation cannot “prove” causality.

In a typical network analysis, all nodes are part of the same “group”. However, in the case of intrateam networks, we are usually interested in the internal workings of multiple subnetworks (teams) across a common task. Thus, a method must be utilized to simultaneously test effects in all groups at the same time—something done with non-relational data through the use of a mixed-effects or multilevel model. *RSiena* provides four different mechanisms for this. First, all teams can be combined into one larger network with structural zeroes forcing ties between teams to be null. Second, all teams can be combined into a *multi-group* project, in which these structural zeroes are essentially created by the software. Third, meta-analysis is possible in which each team is run as a separate network with parameters being combined meta-analytically afterwards. Finally, a random coefficient multilevel analysis can be run using Bayesian estimation. In the first two techniques, an assumption is that all teams will have the same model specification and parameters. With the third technique, all effects are assumed to be random by team—that is, there is no constraint to hold some parameters fixed across teams. With the fourth technique (and similar to traditional frequentist multilevel modeling), some effects can be modeled as fixed (not varying by team) while others can be modeled as random (varying by team). Since the analytical technique for the second stage requires a random effect for each team, either the third or fourth option is possible. The third converged with more success than the fourth, and thus was used for all analyses.

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As a result of the first-stage analysis, each team in the dataset receives a *coefficient of collaboration heterogeneity*, which represents the degree to which collaboration tie creation in the focal team was correlated with ego-alter heterogeneity. The second stage of the analysis then evaluates the bottom-up effect of this collaboration heterogeneity in the team on team performance by including the derived coefficients as predictors (along with control variables) in a standard OLS regression model at the team level with team performance as the outcome. This is similar to empirical Bayes estimates, (cf. Chen, 2005; Joshi & Knight, 2015; Knight, 2013) but instead uses network models rather than mixed-effects or multilevel models.

### Results

Results from the studentized Breusch-Pagan test of heteroscedasticity (see Table 2) indicate that differences in variance are marginally but not consistently significantly predicted by diversity distribution. Gender diversity shows the largest effect ( $\chi^2 = 3.73$ ,  $df = 1$ ,  $p = .05$ ), followed by information diversity ( $\chi^2 = 2.46$ ,  $df = 1$ ,  $p = .12$ ) and ethnic diversity ( $\chi^2 = 0.81$ ,  $df = 1$ ,  $p = .37$ ). When considered all together, the diversity distribution predictors show weak statistical significance in predicting the heteroscedasticity of the model ( $\chi^2 = 6.83$ ,  $df = 4$ ,  $p = .08$ ). Visual examination of the scatterplots (see Figures 1-3) indicate a small increase in performance variance as team diversity increases. In total, these results provide weak support for Hypothesis 1.

Correlations between puzzle completion time and each of the collaboration heterogeneity variables (Table 3) are significant, although heterogeneity of information collaboration appears to increase puzzle completion time (poorer performance) rather than decrease it). Results from the analysis of information diversity (Table 4) indicate the reverse effects that were hypothesized, with increased collaboration heterogeneity across informational differences

leading to an increase in puzzle completion time ( $b = 170.02, p < .10$ ) rather than a decrease. Neither team diversity distribution nor overall collaboration were significantly associated with performance when included in the model by themselves, but overall collaboration led to an increase in puzzle completion time. As we discuss later, this may reflect a difficulty in coordinating mental models when approaching a group with different task-relevant frames. They could also be the result of small sample size, which was reduced by both model convergence issues as well as experimental design. (Only a subset of teams had the necessary information distribution.) As it stands, these results fail to support H2a.

Tests of Hypotheses 2b exhibited results which are more consistent with the hypothesized effects, with passes that crossed gender differences ( $b = -111.83, p < .05$ ) or white/non-white differences ( $b = -100.32, p < .05$ ) being associated with decreased completion times. Passing heterogeneity that crossed Asian/non-Asian lines was also associated with decreased completion times, but the effect was not statistically significant ( $b = -68.69, p = .22$ ). Overall collaboration was only a significant effect when modeled along gender collaboration heterogeneity ( $b = 110.50, p < .10$ ) or white/non-white collaboration heterogeneity ( $b = 98.04, p < .10$ ). Together, these results provide support for H2b.

### **Discussion of Study 1**

Study 1 evaluated the performance of a sample of undergraduate students randomly assigned to teams on a puzzle building exercise and found weak support for Hypothesis 1, no support for Hypothesis 2a, and support for Hypothesis 2b. While the contrived nature of the teams and the task are a disadvantage from the viewpoint of external validity, these characteristics allowed for a controlled environment that eliminates potential environmental

confounds. Further, while the lack of a history or future for these teams is somewhat unrealistic, it does shed some light on the initial relational processes that can occur in new teams

To expand on these findings, Study 2 will examine the same patterns and hypotheses in the applied setting of professional basketball. While retaining the characteristics of objective performance data and unobtrusive measures, this sample examines teams that have both prior relationships and the expectation of future relationships. Further, participants in this setting are highly motivated to perform at the highest possible level, which is a strong test for my hypotheses.

### **STUDY 2: PROFESSIONAL BASKETBALL PLAYERS**

#### **Sample**

For Study 2, game data from the 2013-14 season of the National Basketball Association (NBA) was scraped from the NBA website (<http://nba.com>). (R code for data scraping is found in Appendix 3.) This dataset consists of 482 players split between 30 teams, ranging from 15-20 players per team. Most data are collected at the game level over the course of 82-game regular season. Several facets of these data are relevant for answering the questions posed in this dissertation. First, numerous scholars in the past have noted the usefulness of sports data for analyzing questions relevant to organizations (Day, Gordon, & Fink, 2012; Wolfe et al., 2005). Second, the use of sports data allows for objective and relatively unobtrusive performance measures (Webb, Campbell, Schwartz, & Sechrest, 1966), free of the noise of experimenter or lab effects. Third, basketball is typically considered to be the most team-oriented game of the major American sports. In particular, coordinated efforts are relatively voluntary and discretionary in comparison to more scripted games like American football, thus leaving players more latitude in deciding whether to collaborate or not (Keidell, 1987; Smith & Hou, 2014).

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Fourth, since 2013 the NBA has used special technology in their arenas that tracks player and ball movement at 30 measurements per second. One downstream outcome of this technology is the automation of collecting passing data, including passer and recipient information. Passing is perhaps the best measure of coordination and collaboration in the context of basketball, but it is rarely if ever recorded for labor-intensive reasons—it typically requires counting by hand while watching the game.

This second sample provides several points of similarity and difference relative to the aforementioned lab sample. Both samples share a heavy emphasis on interdependence and feature objective measures of both dyadic collaboration and team performance. Relative to the lab data, the NBA data measure collaboration and performance over a much longer period (six months versus one hour) and with a population that is more motivated to achieve (highly paid athletes versus volunteer undergraduates).

### **Measures**

*Periodicity.* Conceptually, several aggregation methods could be used to convert the real-time NBA data into multiple waves for analysis. First, each game could be viewed as a performance episode, which provides a natural boundary but generates a high quantity of snapshots. Second, data could be aggregated on a weekly basis. However, teams differ widely on the number of games played in a week (from one to five), which inserts a high level of noise into the data. Finally, data could be aggregated on a monthly basis, which would yield the opposite problem from game-wise aggregation by generating a relatively small number of waves (5-7, with an inconsistent number of matches in each period). Given these tradeoffs, a game-level aggregation was chosen, which would ensure that both number of periods and quantity of playtime would be consistent across all teams and waves.

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***Dyad-level dependent variable.*** Collaboration is operationalized as passing at the dyad-game level. A successful pass requires the reciprocated attention and effort of both the passer and the receiver. The receiver must look at the entire court, evaluate the positioning of friendly and enemy players, find an open space, and signal to the passer that he is open. Similarly, the passer must see the signals of all potential targets, the potential interface of the opposing players, and properly time a pass to reach a receiver in stride. If either party fails to fully attend to the details of the play, the pass will be unsuccessful, and the ball will most likely end up in the hands of the opposing team. Heterogeneity of this passing is measured using the same formula as in Study 1.

A particularly important feature of passing in basketball for the study of collaboration and team outcomes is that it is fundamental to team success. If a basketball team were known for having an extremely selfish player, it would be very easy for opposing defenses to overwhelm that player and prevent scoring. Further, a passed ball moves much faster than a person can, meaning that the ball can move around defensive arrangements more efficiently when passed rather than dribbled. Thus, success in a basketball setting requires well-coordinated passing, or “complex interdependence” (Thompson, 1967). As in the lab study, this measure will be dichotomized for analysis.

While box score data (e.g. points or rebounds) are readily available on many online sources, including the official website of the NBA, passing data is much harder to come by. However, dyadic data was found on the official website on a per-player, per-game basis (one page per player-game). These data were scraped from the website (code in Appendix 1) and reformatted into an edgelist that showed passer, receiver, game, and number of passes. This was merged with other supplemental data as described below to generate the full dataset.

**Team-level dependent variable.** At the team level, a substantive measure of team performance is needed. While win-loss performance is a natural first inclination due to its function as the ultimate measure of success in competitive sports, it is also a noisy measure due to its fundamental binary nature. If a team loses by one point, the game is considered a loss. However, if that same team had scored just two more points, it would have won by a point. Thus, we follow Kubatko and colleagues (2007) and operationalize team performance as *offensive rating*, which conceptually captures the pure offensive performance of the team independent of the win/loss record. Computationally, offensive rating is based on the number of points scored per game. Points are a suitable measure of performance because they are the final goal of any offensive play in basketball. Rather than use points in their raw form, the offensive rating measure normalizes them per 100 possessions. In basketball (as in many other sports), each team in a given game will have possession of the ball an equal amount of times (since teams trade possession back and forth). However, the number of possessions differs greatly between games, making the typical “per game” standardization misleading. These possessions are not typically recorded as part of a standard box score, but they can be easily inferred with the following formula (Kubatko et al., 2007):

$$POSS_t = .976 ( FGA_t - OR_t + TO_t + .44 * FTA_t ),$$

where  $FGA_t$  is the number of shots attempted by the focal team,  $OR_t$  is the number of focal team offensive rebounds (shots that are missed and then reacquired by the shooting team),  $TO_t$  is the number of focal team turnovers (plays that results in lost possession of the ball), and  $FTA_t$  is the number of focal team free throws attempted (number of penalty shots taken).

**Diversity dimensions.** Several dimensions of diversity, both related and unrelated to the task, were considered. For the former, player salary and affiliation with a high-level professional

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agent (responsible for securing work contracts for the athlete) are both used to infer player quality. For the latter, player nationality and college affiliation (or lack thereof) are used as task irrelevant categories that players may use to categorize themselves and others. All of these dimensions were collected from publicly available sources.

**Controls.** Using the same formulas as in Study 1, network measures of outdegree density and reciprocity are used as standard controls for predicting tie creation in dyad-level models. In addition, player absence is accounted for due to either team roster changes (e.g. midseason trades or free agent signings) or bench time (usually due to injury or coaching decisions). Thus, only tie creation or dissolution is only evaluated for players that actually participated at some point during the focal contest. At the team level, total passing and diversity distribution are used as controls as in Study 1. Also, since (a) contests are played against other teams of varying skill and (b) schedules are uneven, in that some teams play each other more than others, there is variance in task difficulty at the team level that is attributable to the competition. Thus, an opponent's defensive rating will be used as a control at the team level.

### **Analysis**

Hypothesis 1 is evaluated in the same manner described in Study 1. Hypotheses 2a and 2b also utilize the same two-stage analytical approach that was detailed in the description of Study 1 (the sequential use of SAOMs and OLS models). One technical difference that added substantial modeling complexity is the inclusion of network joiners and leavers to account for roster changes or player benchings. This contingency is modeled by supplying the *RSiena* model with a list of games in which the player appeared. However, this procedure requires the estimation of an additional 82 parameters in each model (one for each time period) on top of the 3 or 4 primary effects of interest effects modeled if team membership is unvarying.

### **Results**

Results from the studentized Breusch-Pagan test indicate substantial heteroscedasticity in the relationship between team diversity and team performance (except for agent diversity). The  $p$  values for these tests are weak, but it is unclear whether this is representative of low power (only 30 teams), a small effect, or both. When all diversity measures are included in the same model, the studentized Breusch-Pagan test is consistent with findings from the individual models. Visual inspection of the scatterplots does not clearly indicate that performance variance is increasing as diversity increases, although again this may be a limitation of the small sample size. Together, these analyses provide weak support for H1.

Pairwise correlations between team performance and team diversity or collaboration heterogeneity (Tables 9–13) are non-significant across all measures. This pattern of non-significance is replicated in the regression models, which indicate little to no effect of collaboration heterogeneity on team performance when controlling for overall collaboration, opponent defensive rating, and levels of team diversity. In whole, these results offer no support to Hypotheses 2a or 2b.

### **Discussion of Study 2**

Study 2 evaluated the performance of professional basketball teams relative to the heterogeneity of their collaboration patterns. Weak support was found for Hypothesis 1, while Hypotheses 2a and 2b were unsupported. While these results may reflect the true relationships, there are confounding factors that could be addressed, possibly yielding different findings. In the general discussion, I discuss these limitations along with potential future directions.

## **GENERAL DISCUSSION**

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Across two samples, I evaluated the relative impact that team diversity and the heterogeneity of team collaboration have on team performance in interdependent tasks. Moderate support was found for the hypothesis that variance of team performance changes across levels of team diversity. The laboratory study generally supported the idea that it is collaboration heterogeneity, and not team compositional heterogeneity, that predicts performance in these settings, but the archival basketball study did not replicate this finding. The combination of these findings provide guidance for future research, either in developing new theoretical insights, addressing possible weaknesses in one or both the studies' research designs, or testing other relationships in the emergent network model of team diversity. I discuss each of these topics in succession below, adding to the largely theoretical discussion that was provided at the end of Chapter 2.

### **Theoretical implications for research on team diversity and related fields**

Of primary importance, the findings described here provide some initial support for my central claim that collaboration heterogeneity in teams is critical to team performance on interdependent tasks. When considered in conjunction with my broader theoretical model described in Chapter 2, this continues to suggest that it is the processes associated with interpersonal differences within teams—rather than simply the team composition itself—that is primarily responsible for variance in team outcomes. This not only has implications for the study of team diversity specifically, but any related fields that may use a measure of team diversity as a predictor of important outcomes (e.g. top management teams, corporate governance). The common thread through these fields is that the *composition* of the team is used to infer the *dyadic behaviors and processes* of the team, an attribution which these findings call into question. While composition can certainly play a role in many settings, that role may often be as a

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necessary condition rather than a sufficient one. Rather than using team composition as a proxy for team behavior, I encourage scholars to consider measuring the inferred behaviors as well to determine whether composition alone can explain the phenomenon in question.

Second, these findings have implications for the faultline and subgroup literature. As with the broader team diversity literature, these theoretical perspectives have tended towards compositional approach rather than a relational one. If patterns of dyadic behavior can explain group outcomes above and beyond the impact of compositional diversity, then the same is likely in the study of faultiness and subgroups. Work is already heading in this direction, at least in terms of considering of dyadic ties within larger collectives (Carton & Cummings, 2012, 2013; Ren, Gray, & Harrison, 2014), and my findings indicate that microdynamics should continue to be explored in these areas.

Third, the pattern of results is interesting when placed next to contemporary research on equity and inclusion. While the theory described in Chapter 2 and the empirical work outlines in this chapter is decidedly “dimension neutral”, the fact that patterns involving gender and ethnicity played a substantial role in determining team performance suggests further work surrounding the directionality of that heterogeneity. When considered alongside work on collective intelligence that suggests gender may be correlated with social sensitivity (Woolley, Chabris, Pentland, Hashmi, & Malone, 2010), perhaps there are performance differences based on the directionality of the gender heterogeneity (male-to-female vs. female-to-male). While this hypothesis needs to be theoretically balanced with the philosophical question of essentialism (Ho, Roberts, & Gelman, 2015; Tadmor, Chao, Hong, & Polzer, 2013), it nonetheless poses an intriguing empirical test for future work.

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Fourth, these results may suggest further boundary conditions for the model described in Chapter 2. First, the directional difference between task related and unrelated dimensions in Study 1 suggest that the time horizon of the task and the longevity of the team may play a role in when performance benefits from these two categories of differences emerge, if they in fact appear at all. The constrained timeline of a laboratory study perhaps did not provide the necessary time for mental models to align based on information diversity, whereas there was plenty of time for implicit biases to affect the optimality of passing patterns. Second, the non-significant findings from Study 2, if not related to solvable methodological issues, may represent an upper limit to the applicability of my theory in Chapter 2. If teams are highly trained and incentivized to perform at their absolute maximum potential, then the observed variance of performance due to suboptimality or implicit bias should be much lower.

Fifth, my use of a heteroscedasticity test as a relevant hypothesis test rather than merely a statistical assumption of regression models can be particularly useful in scenarios which, like the diversity-performance relationship, exhibit equivocal findings over a large set of studies. Analyzing changes in variance across a predictor or set of predictors can be a helpful exploratory analysis to determine if other variables (particularly ones related to the predictors) can be used to explain the outcome in question.

Finally, my hope is that this empirical research utilizing SAOMs and emergent causation provides a roadmap for extending a microdynamic approach to other teams research. For example, this perspective can add to our knowledge regarding the evolution of conflict in teams (Jehn, Rispen, Jonsen, & Greer, 2013). What causes a fight among two team members to spread? Can a third-party broker reconciliation between two conflicting parties, and if so, under what conditions? As another example, theory on emotional contagion could be evaluated from a

microdynamic perspective. Do expressions of gratitude build upon one another to change the emotional climate of the group (Fehr, Fulmer, Awtrey, & Miller, 2017)? Do they provide a modeling influence to other members in the team? These kinds of questions can be answered theoretically with a microdynamic perspective and empirically with two-stage analyses like the one I outlined earlier.

### **Limitations**

There are several empirical limitations that may obfuscate or attenuate the predicted relationship. First, the sample size in both studies is relatively small. While this is not an uncommon problem in teams research, it means that these samples are relatively underpowered. Further, the samples represent two extremes in terms of performance demands and applicability to more common organizational settings. On one hand, the laboratory study consists of a group of undergraduates with no collective past or future and very little incentive to perform at optimal levels. On the other hand, the basketball players are embedded in an intense culture of competition and represent months of training together for the highest possible performance. Samples from a wider variety of settings will be needed to determine how this confound affects the results from these studies.

Another limitation in both studies pertains to diversity dimension selection. While I was careful to sample from dimensions that were presumably either task relevant or task irrelevant, I have no way of knowing for certain *a priori* if these characteristics function purely in this manner. Further, the selection of other dimensions may reveal other patterns, and salience of any dimension (even it exists as a source of objective differentiation in the team) is subject to identity cues that make it rise to the surface for perceivers (as described in Chapter 2). Thus, further work

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needs to be done both with expanding the set of dimensions examined as well as addressing the question of perceiver salience.

The use of these measured diversity dimensions (apart from the manipulation of information diversity in Study 1) also creates difficulties in causal inference. An unobserved variable could be accounting for both the existence of diversity in the team as well as the team's performance level. For example, the correlation between team nationality diversity and team offensive rating could indicate that a successful team is more attractive to the best (foreign) players, rather than the nationality of the team being a driver of performance. However, the chance of omitted variables is somewhat reduced since (a) it is the heterogeneity of collaboration that is the focal construct (and not team diversity itself) and (b) team diversity is controlled for in all analyses. Further work with experimental designs or more robust archival samples would provide further evidence in this regard.

The use of SAOMs creates some analytical constraints across both studies. First, although collaboration measures in both studies were count variables, they had to be analyzed as binary variables. This dichotomization is a common limitation in network studies, but it requires a subjective choice on the part of the analyst regarding where to split the continuous variable. Second, while data were observed and coded in real-time, they needed to be analyzed in a set of discrete timeframes or "waves". The periodicity of these waves was again a subjective analytical choice, but empirical techniques are emerging that address this challenge in a more robust quantitative fashion (McCulloh, Johnson, & Carley, 2012; Wei & Carley, 2015). Finally, as mentioned earlier in the section on analysis, SAOMs are only one of a family of network models that allow for prediction of tie formation and may be overly complex for the hypotheses

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addressed in this chapter. Further work comparing and contrasting these approaches could be useful for triangulating the findings described here.

Regarding the laboratory study specifically, several research design elements can be improved with further work. First, the variance of team size (between four or five participants) introduced extra noise into the data that could have been eliminated by holding team size constant. Second, demographic differences in teams could be manipulated to create more reliable evaluations of these dimensions than using measures of diversity. Third, and as is true of much teams research in comparison to individual-level research, sample size was limited due to the sheer number of participants needed to assemble a team. Using a laboratory with more input, or designing online versions of this exercise, could circumvent this bottleneck. Finally, these relationships could be a function of the particular task, and other exercises should be used to replicate the findings from Study 1.

The findings from the basketball study reflect both sample limitations, which are likely unresolvable, as well as some substantial design issues that could be addressed with further work. Regarding the former, this sample reflects a very strong test of my hypotheses. Professional athletes are highly motivated to perform in the most efficient and effective manner possible, and most participants in this sample had played together for a substantial amount of time. As such, they are not likely to exhibit the collaboration inefficiencies that are theorized. This possibility is partially supported by the small average levels of collaboration heterogeneity. If collaboration heterogeneity plays a relative small role in such a hyper-competitive environment, then it is likely that more data would need to be collected, both in terms of sample size and in terms of confounding variables that could be used as controls.

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Additionally, one source of unaddressed variance in the basketball sample is the amount of shared playing time that players had with each other, both within games and across seasons. For the former, this could be solved with new data collection that uses game logs (which includes substitutions and thus can reconstruct the active players at any given second of the game) rather than aggregated game statistics. This would then need to be paired with the passing data to form a composite dataset that allows for shared minutes as a control. For the latter, shared team tenure could be added as a control based on previously collected data regarding roster moves.

From a design perspective, there are issues that could be later addressed to better evaluate these hypotheses in the basketball data. Beyond collecting more years of data or further omitted variables, alternative outcomes could be considered beyond year-long offensive rating. Mixed-effects models could be used to examine these questions at the game level, comparing the relationship between collaboration heterogeneity and team offensive rating in each contest rather than aggregating over the year. Finally, it could be that the use of SAOMs are too complex for this kind of analysis, and a simpler model could accomplish the same test with less analytical overhead.

### **Future work on the theoretical model from Chapter 2**

Although the empirical studies described in this chapter provide an initial look at two foundational hypotheses from the theoretical model outlined in Chapter 2, testing all parts of the model will require a variety of methods and research designs. Traditional experimental or survey studies can establish many of the linkages from a cross-sectional perspective, with a primary opportunity being an evaluation of identity cues as the mechanism that both connects interindividual differences to collaboration preferences as well as connects emergent

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collaboration microstructures to future collaboration preferences. Manipulating diversity configurations and collaboration patterns will allow for detailed insights regarding the interplay of these predictors as they affect identity cues and collaboration.

Further experimental work would also be useful in refining the study of the hypotheses posited in this chapter. For example, it may be that the hypothesis that performance variance grows with team diversity is too simple. Qualitative research suggests that diversity has a curvilinear relationship with average team performance (Earley & Mosakowski, 2000), and it could be that variance follows a similar pattern. At extremely low levels of diversity, the lack of complementary skills could have a stronger effect than perceived high affective value, whereas at extremely high levels the lack of homophily could be more powerful than the uniqueness that diversity brings. By manipulating this more precisely along a wide continuum of diversity levels, this idea could be tested directly.

Archival work provides the opportunity to examine long time spans and thus multiple iterations of the emergent cycle described in Chapter 2. In fact, this was a strength of the NBA data, which can continue to provide insights beyond what has been analyzed in this chapter. Data sources such as email or forum archives from settings such as open source software engineering can also provide unobtrusive measures of collaboration while being closer to an organizational setting than a professional sports sample. This kind of study will be best at addressing the long-term effects of collaboration patterns, particularly if a setting is found that allows the examination of a team from its initial stages.

Organizational field studies are ultimately essential to test this theory. This would be best done in a full-cycle manner (Chatman & Flynn, 2005), which would allow for iteration between rich understanding of an individual's experience of diversity salience in the workplace alongside

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more generalized knowledge about how these experiences affect team and organizational performance. Despite their limitations, sociometric sensors could be used to provide highly granular quantitative data regarding the positioning of subjects throughout a workday. This could then be supplemented with diary data or interviews to provide better insights regarding how these ideas play out in a natural setting.

Finally, the propositions regarding emergence and steady states could be evaluated using simulation techniques such as agent-based models (Fioretti, 2013). These methods model the outcomes of behavior based on a set of simple rules and probabilities. While simulations clearly lack external validity by themselves, they can be paired to non-simulated data for the sake of comparison. The flexibility and inherently longitudinal nature of these methods may represent one of the best ways of testing the proposed effects of emergent cycles over time.

### **Conclusion**

Causal connections between team diversity and team performance, while maintaining an intuitive presence in our minds, remain elusive to validate in various real-world settings. In this dissertation, I have evaluated some of the intervening processes in this relationship that have remained a black box in much of the prior research. My theory and findings suggest that heterogeneity does indeed matter to team performance, but that these effects are dependent on the way differences are utilized rather than their mere existence. Ultimately, I hope that this both affirms the idea that “something is going on” while at the same time acknowledges that much more work needs to be done to understand how the differences between us affects team and workplace outcomes.

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## FIGURES AND TABLES

Table 1: Summary of studies

<b>Nature of sample</b>	Broken Squares (lab)	NBA game data (archival)
<b>Teams</b>	44	30
<b>Mean team size</b>	4.4 (194 participants)	16.1 (482 players)
<b>Time periods</b>	Minute (up to 15 in total)	Game (82 in total)
<b>Team formation?</b>	Yes	No
<b>Dyadic collaboration</b>	Piece passing between members	Passes between players
<b>Team performance</b>	Time to completion	Offensive rating (points scored per 100 possessions)
<b>Diversity dimensions</b>	Measured: Ethnicity, gender Manipulated: Information, nominal grouping, seating	Nationality, college conference/no college, salary, agent
<b>Controls</b>	Dyadic level: Outdegree density, reciprocity Team level: Total passes, team diversity	Dyadic level: Outdegree density, reciprocity, player availability Team level: Opponent difficulty, total passes, team diversity

**Table 2: Results of studentized Breusch-Pagan test for heteroscedasticity for Study 1**

	Gender	Ethnicity	Information	All
Test statistic	3.73	0.81	2.46	6.83
<i>df</i>	1	1	1	4
<i>p</i>	0.05	0.37	0.12	0.08

N = 44; Dependent variable: Team performance; Blau's index used for diversity measure

**Figure 1: Scatterplot of team gender diversity and team performance**

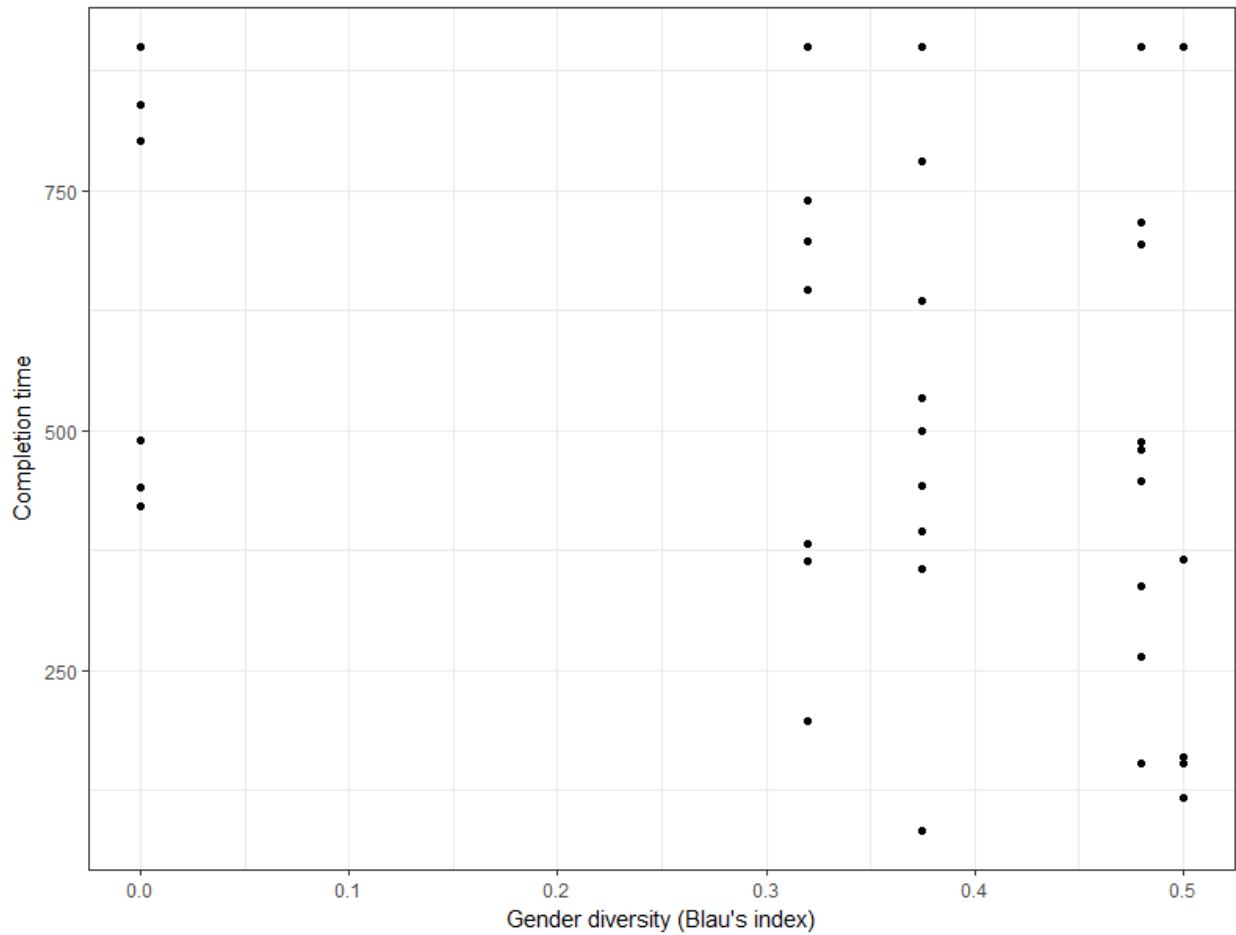


Figure 2: Scatterplot of team ethnic diversity and team performance

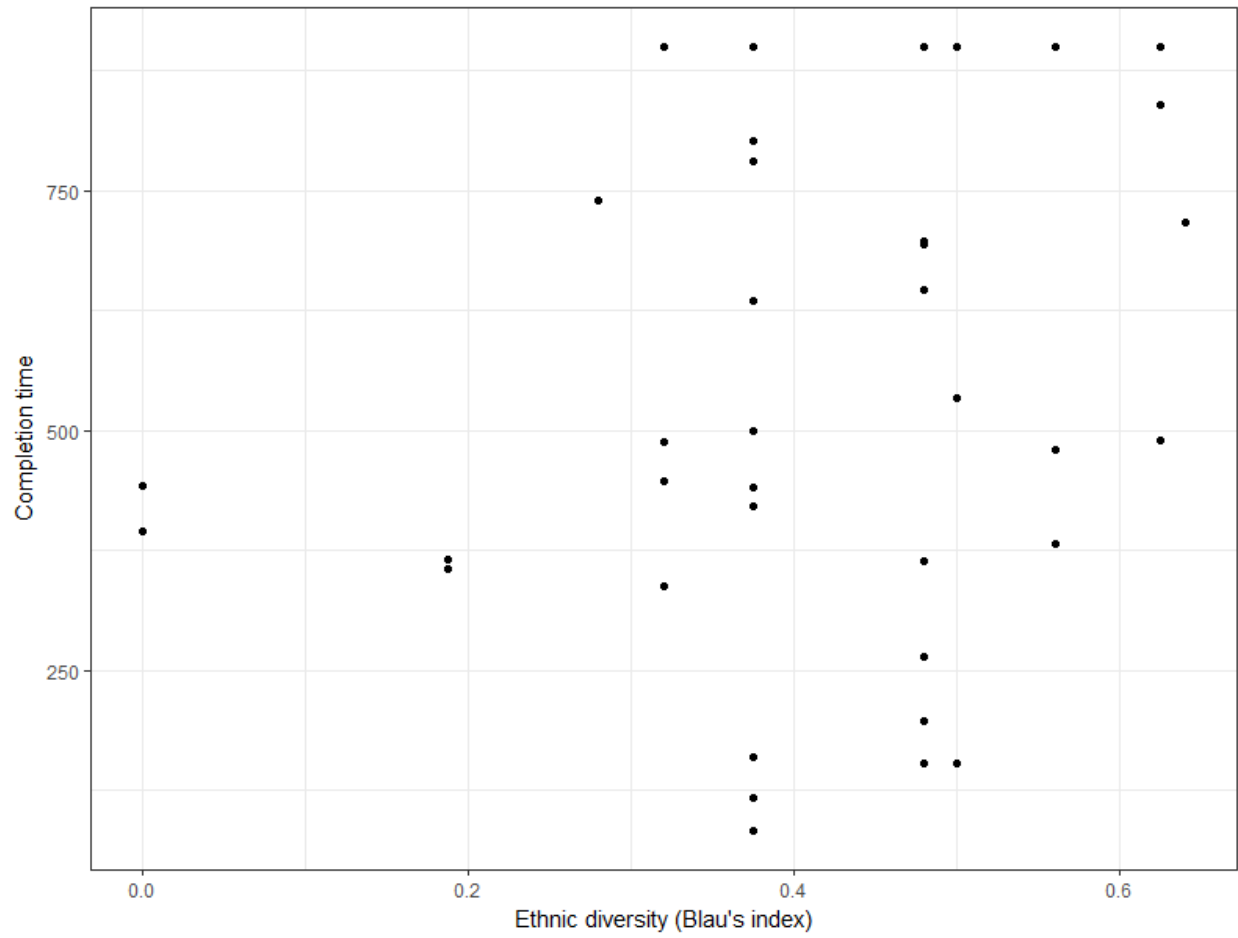
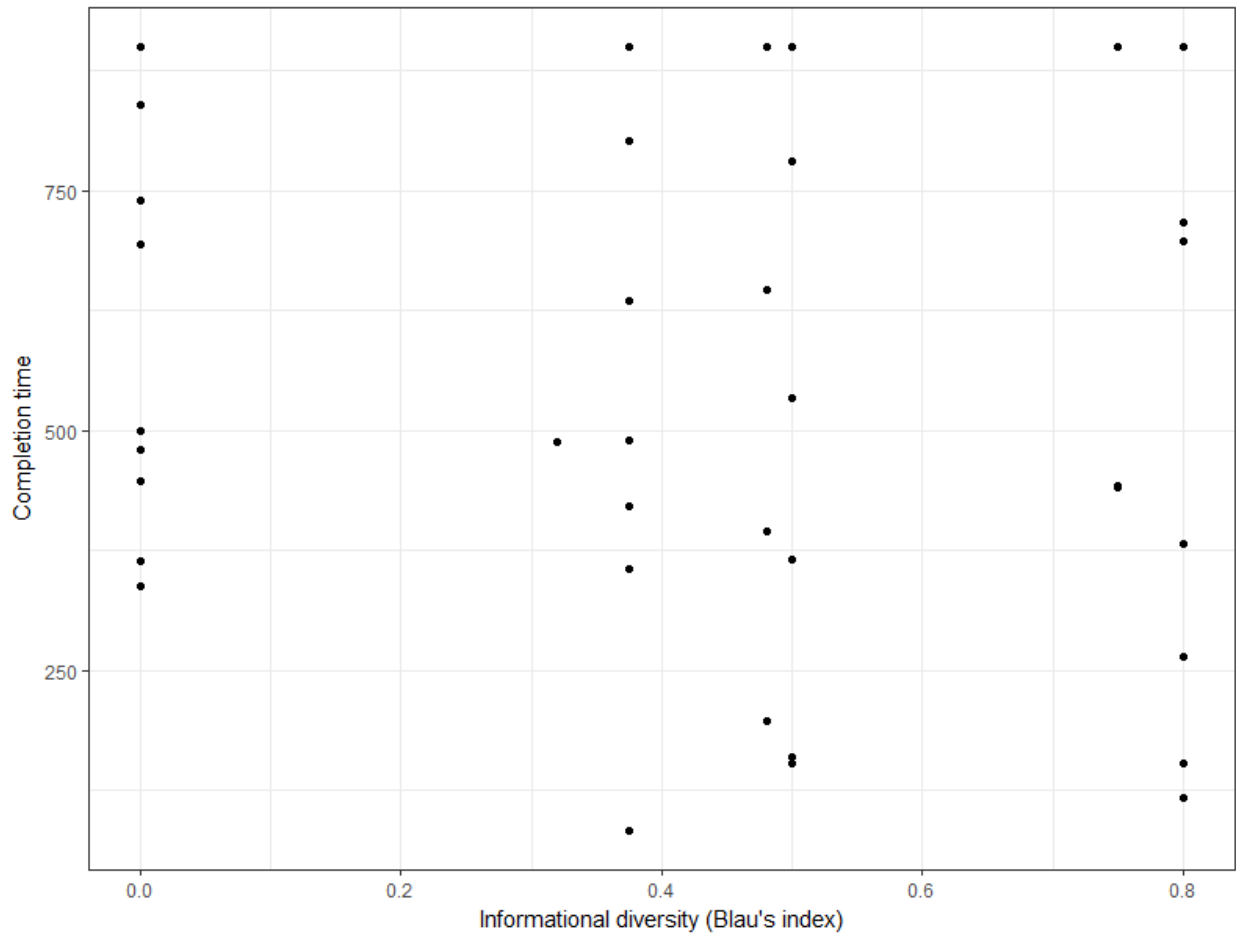


Figure 3: Scatterplot of team information diversity and team performance



**Table 3: Team-level correlation matrix for Study 1**

	<b>M</b>	<b>SD</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>
1. Overall collaboration	29.0	17.43								
2. Team gender diversity	0.36	0.16	.27							
3. Team ethnic diversity	0.42	0.14	.07	-.06						
4. Team information diversity	0.41	0.28	-.36	-.01	-.11					
5. Gender collaboration heterogeneity	-1.02	8.96	.16	-.22	-.14	.20				
6. White/not white collaboration heterogeneity	-1.35	12.43	.17	-.15	-.10	.23	.98			
7. Asian/not Asian collaboration heterogeneity	0.93	3.76	-.36	.11	-.05	.07	.90	.94		
8. Information collaboration heterogeneity	1.57	5.11	-.30	.17	.31	.00	-.05	-.07	.32	
9. Puzzle completion time	586.64	273.19	.21	-.12	.26	-.16	-.37	-.35	-.33	.30

N = 44 teams; correlation values > .30 are  $p < .05$

**Table 4: Results of linear regression models for Study 1: Information**

	<b>Model 0</b>		<b>Model 1</b>		<b>Model 2</b>	
Intercept	481.63 ***	(84.98)	564.12 ***	(63.65)	495.66 ***	(69.24)
Overall collaboration	3.17	(2.52)	48.09	(65.93)	150.33 †	(74.68)
Team info. diversity			-49.96	(66.25)	15.90	(74.15)
Collaboration heterogeneity					170.02 †	(79.72)
$R^2$	0.04		0.07		0.41	
Number of teams	38		14		14	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

Number of teams dependent on network model convergence

**Table 5: Results of linear regression models for Study 1: Gender**

	<b>Model 1</b>		<b>Model 2</b>	
Intercept	569.16 ***	(43.21)	504.49 ***	(63.55)
Overall collaboration	70.14	(45.31)	110.46 †	(53.63)
Team gender diversity	-52.86	(43.31)	47.35	(109.42)
Collaboration heterogeneity			-111.83 *	(51.51)
$R^2$	0.08		0.29	
Number of teams	38		25	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

Number of teams dependent on network model convergence

**Table 6: Results of linear regression models for Study 1: Ethnicity**

	<b>Model 1</b>		<b>Model 2 (White)</b>		<b>Model 2 (Asian)</b>	
Intercept	575.28 ***	(42.10)	532.16 ***	(48.35)	566.58 ***	(55.54)
Overall collaboration	49.67	(42.76)	98.04 †	(49.60)	43.53	(60.07)
Team ethnic diversity	74.47 †	(41.67)	97.94 †	(54.42)	87.20	(58.71)
Collaboration heterogeneity			-100.32 *	(46.09)	-68.69	(54.46)
$R^2$	0.07		0.31		0.21	
Number of teams	38		28		25	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

Number of teams dependent on network model convergence

**Table 7: Results of studentized Breusch-Pagan test for heteroscedasticity for Study 2**

	Nationality	US/Foreign	Top agent	College	Salary	All
Student BP	4.51	3.62	0.04	3.68	3.34	10.35
<i>df</i>	1	1	1	1	1	5
<i>p</i>	.03	.06	.83	.06	.07	.07

N = 30; Dependent variable: Team performance

Blau's index (or coefficient of variance for salary) used for diversity measure

**Figure 4: Scatterplot of team nationality diversity and team performance**

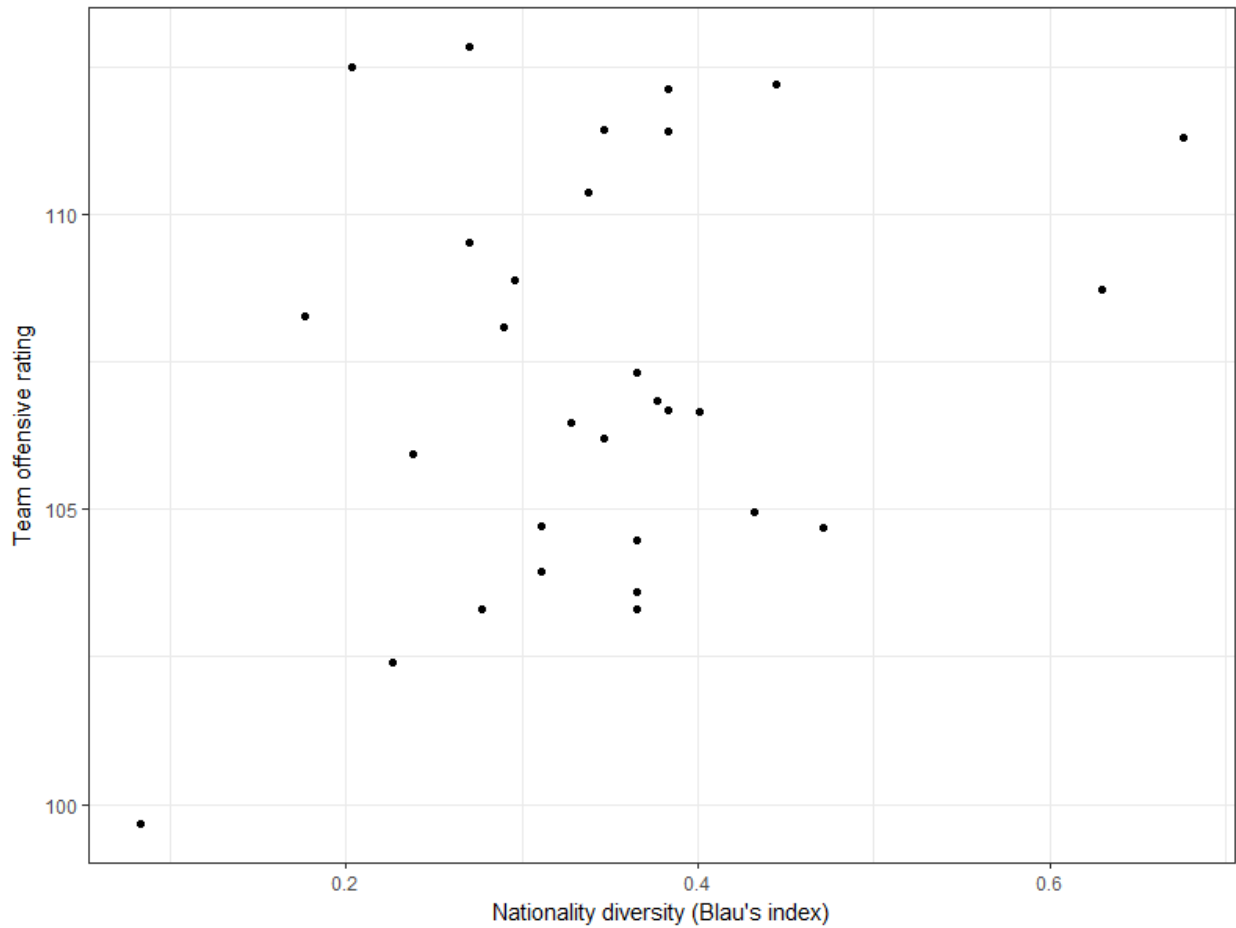
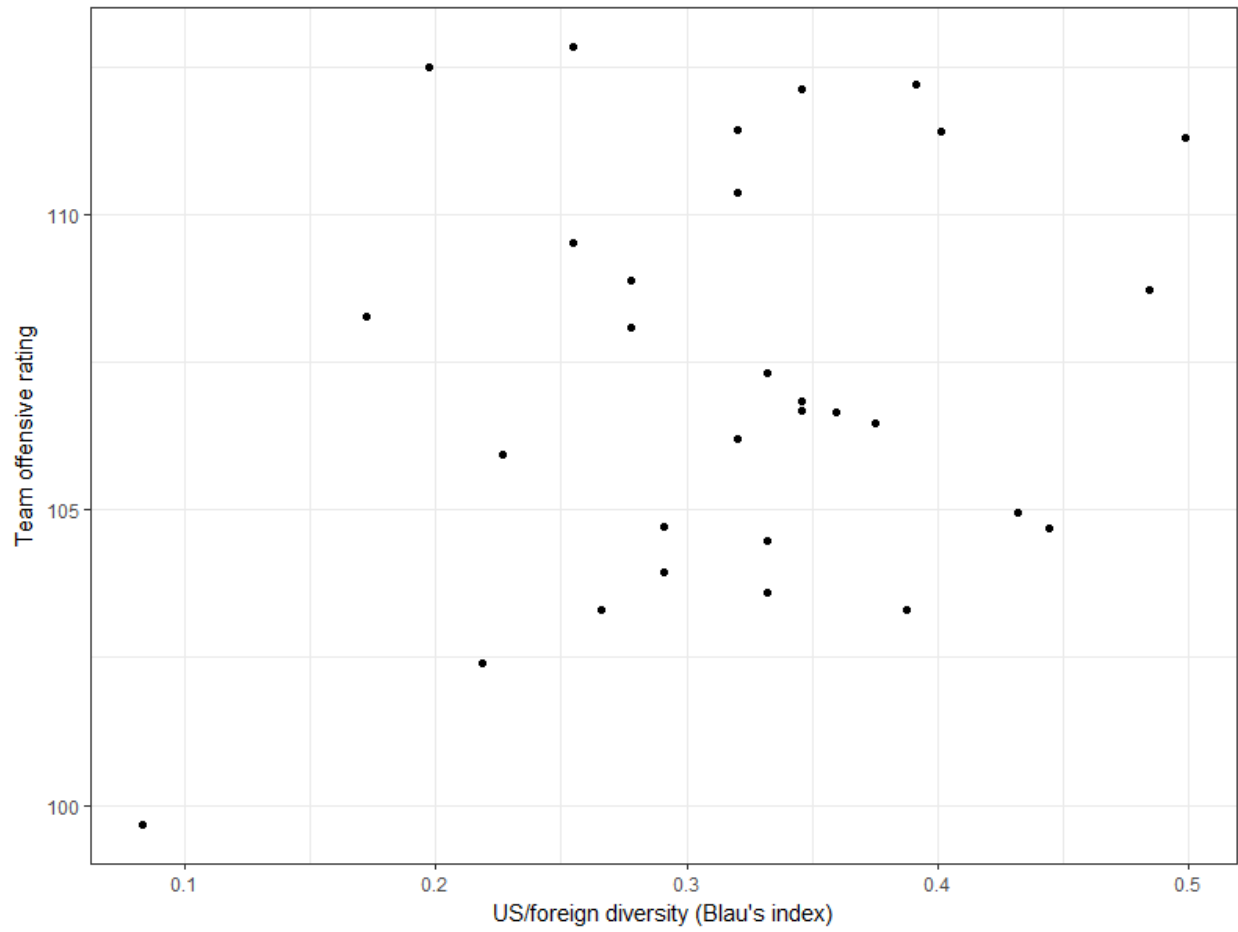


Figure 5: Scatterplot of team US/foreign diversity and team performance



**Figure 6: Scatterplot of team college diversity and team performance**

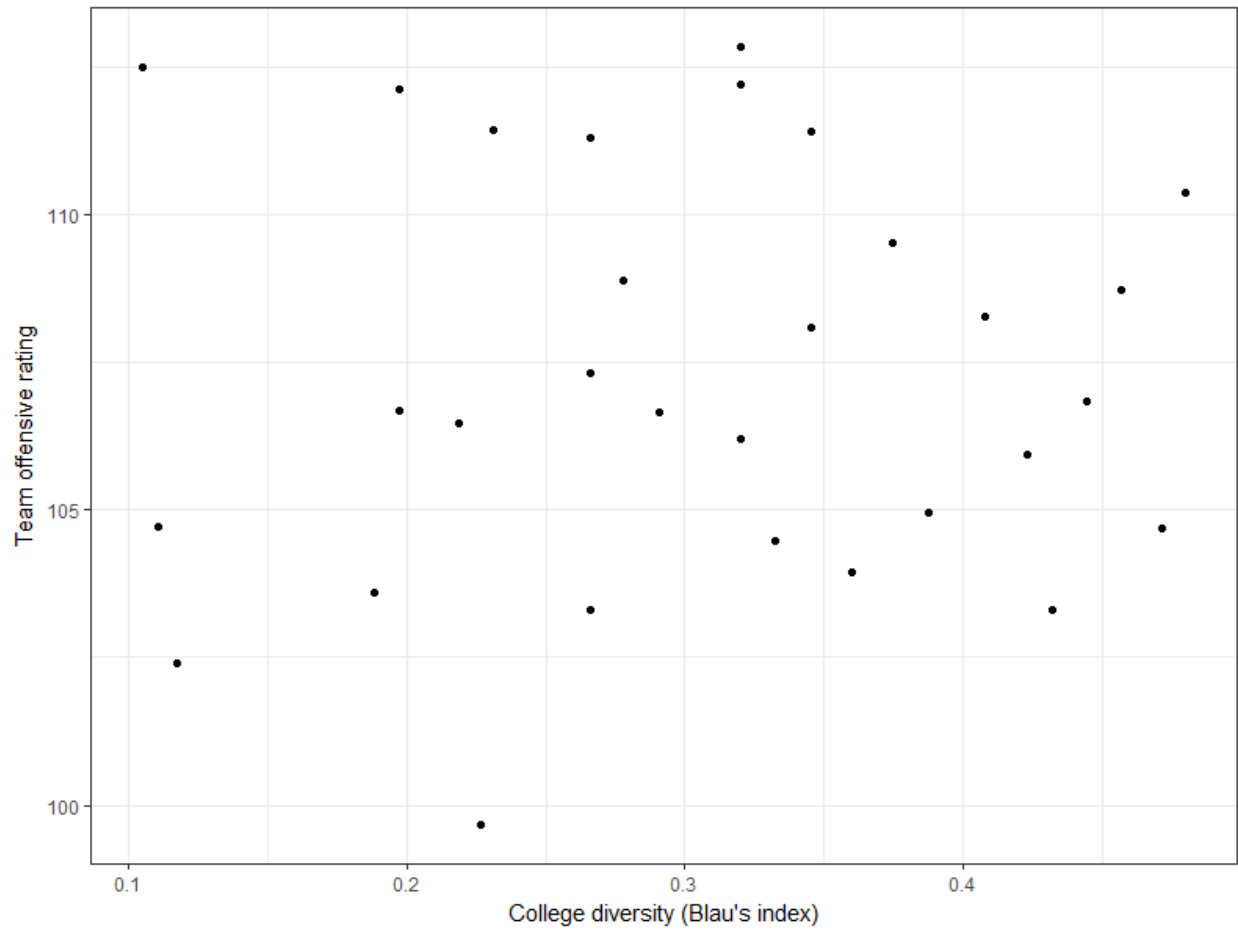


Figure 7: Scatterplot of team agent diversity and team performance

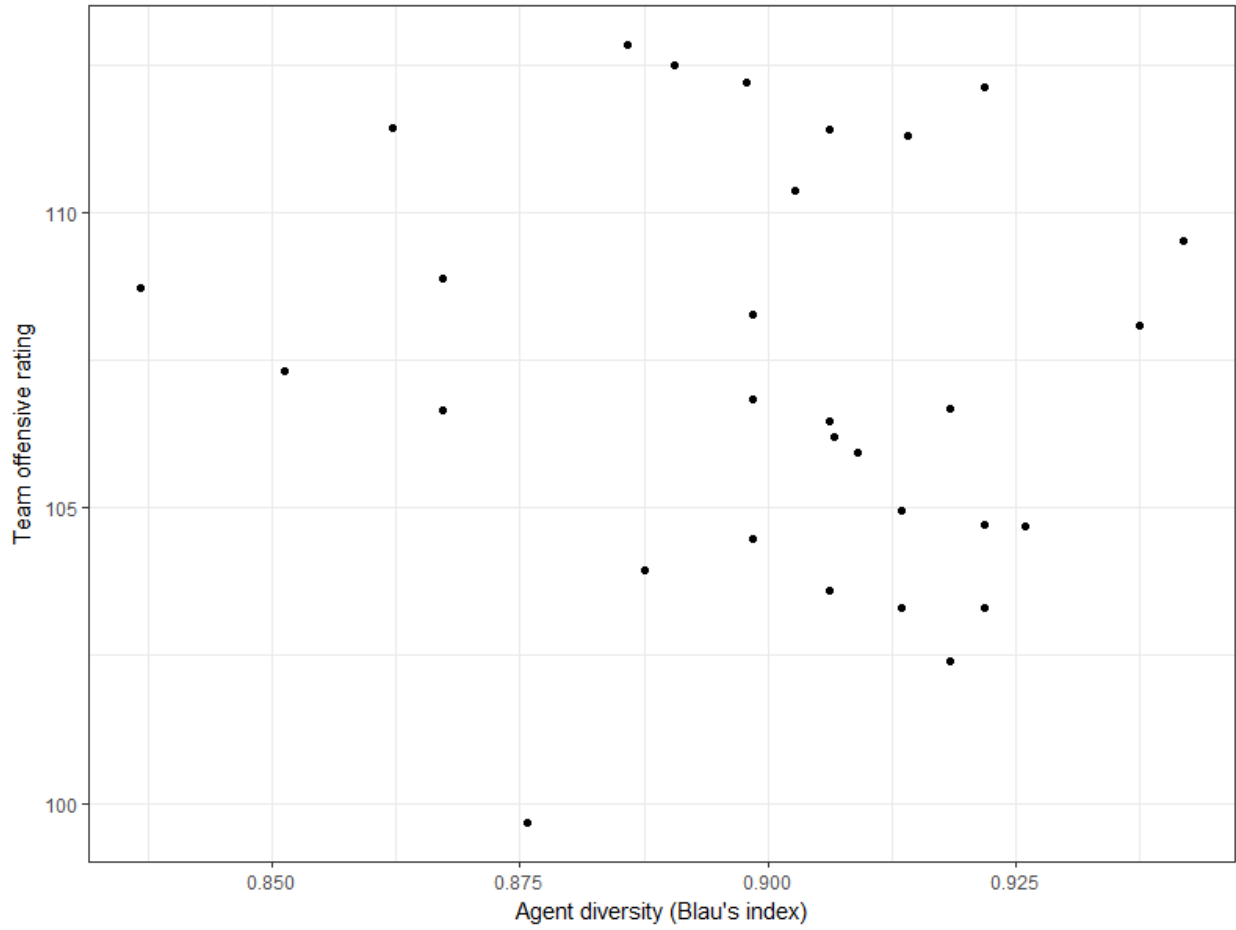
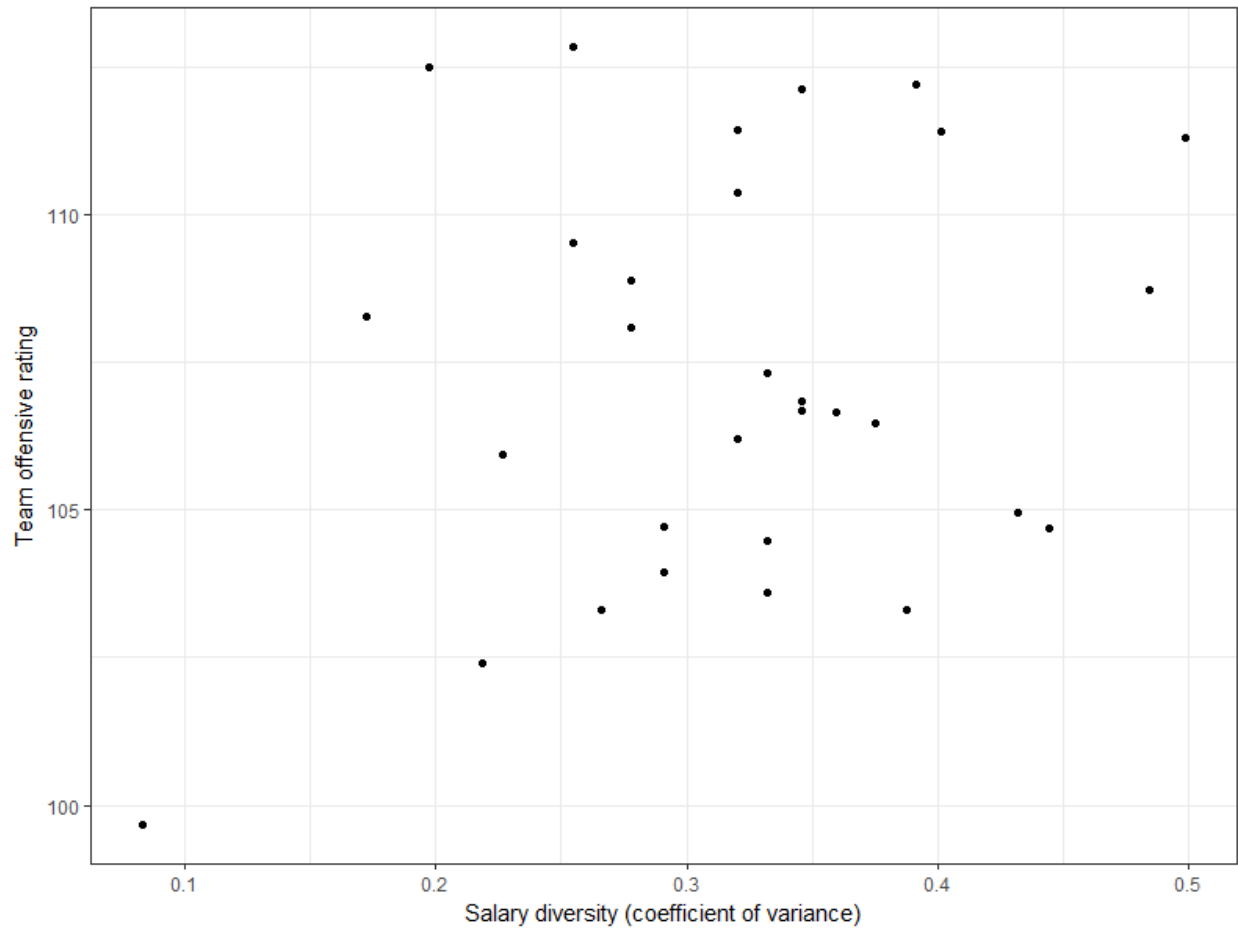


Figure 8: Scatterplot of team salary diversity and team performance



**Table 8: Team-level correlation matrix for Study 2**

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Overall collaboration	24018	1815												
2. Opponent defensive rating	-107.26	0.16	-.04											
3. National diversity	0.35	0.12	.37	-.31										
4. US/foreign diversity	0.32	0.09	.28	-.28	.95									
5. College diversity	0.31	0.11	-.06	-.19	.27	.31								
6. Agent diversity	0.9	0.02	-.13	-.02	-.11	-.01	-.01							
7. Salary diversity	1.11	0.23	.05	.21	-.09	-.04	-.02	.09						
8. National collaboration heterogeneity	-0.11	0.24	.16	-.25	.48	.46	.26	-.01	-.19					
9. US/foreign collaboration heterogeneity	-0.11	0.22	.11	-.20	.33	.38	.27	-.01	-.17	.94				
10. College collaboration heterogeneity	0.1	0.39	.10	.40	-.03	-.02	-.11	-.02	-.19	.04	.10			
11. Agent collaboration heterogeneity	-0.01	0.1	.03	.41	-.19	-.21	-.36	.00	-.30	-.06	-.07	.39		
12. Salary collaboration heterogeneity	-0.84	2.48	-.19	-.40	-.04	-.03	.21	-.06	.17	.01	-.03	-.93	-.44	
13. Team offensive rating	107.29	3.46	-.17	-.23	.28	.24	.04	-.13	.13	-.02	-.12	-.26	-.03	.18

N = 30 teams; correlation values > .36 are  $p < .05$

**Table 9: Results of linear regression models for Study 2: Nationality**

	<b>Model 0</b>		<b>Model 1</b>		<b>Model 2</b>	
Intercept	107.29 ***	(0.63)	107.29 ***	(0.60)	107.29 ***	(0.60)
Overall collaboration	-0.63	(0.64)	-1.08	(0.66)	-1.09	(0.66)
Opponent defensive rating	-0.81	(0.64)	-0.44	(0.65)	-0.53	(0.65)
Team diversity			1.24 †	(0.70)	1.59 *	(0.76)
Collaboration heterogeneity					-0.79	(0.70)
$R^2$	.09		.19		.22	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

N = 30 teams

**Table 10: Results of linear regression models for Study 2: US/Foreign**

	<b>Model 1</b>		<b>Model 2</b>	
Intercept	107.29 ***	(0.62)	107.29 ***	(0.61)
Overall collaboration	-0.88	(0.65)	-0.88	(0.64)
Opponent defensive rating	-0.56	(0.65)	-0.66	(0.65)
Team diversity	0.91	(0.68)	1.24 †	(0.71)
Collaboration heterogeneity			-0.93	(0.67)
$R^2$	.14		.21	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

N = 30 teams

**Table 11: Results of linear regression models for Study 2: College**

	<b>Model 1</b>		<b>Model 2</b>	
Intercept	107.29 ***	(0.64)	107.29 ***	(0.64)
Overall collaboration	-0.64	(0.65)	-0.57	(0.66)
Opponent defensive rating	-0.82	(0.66)	-0.57	(0.72)
Team diversity	-0.06	(0.66)	-0.08	(0.67)
Collaboration heterogeneity			-0.62	(0.72)
$R^2$	.09		.11	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

N = 30 teams

**Table 12: Results of linear regression models for Study 2: Agent**

	<b>Model 1</b>		<b>Model 2</b>	
Intercept	107.29 ***	(0.63)	107.29 ***	(0.64)
Overall collaboration	-0.71	(0.65)	-0.72	(0.66)
Opponent defensive rating	-0.82	(0.64)	-0.95	(0.72)
Team diversity	-0.55	(0.65)	-0.55	(0.66)
Collaboration heterogeneity			0.30	(0.71)
$R^2$	.11		.12	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

N = 30 teams

**Table 13: Results of linear regression models for Study 2: Salary**

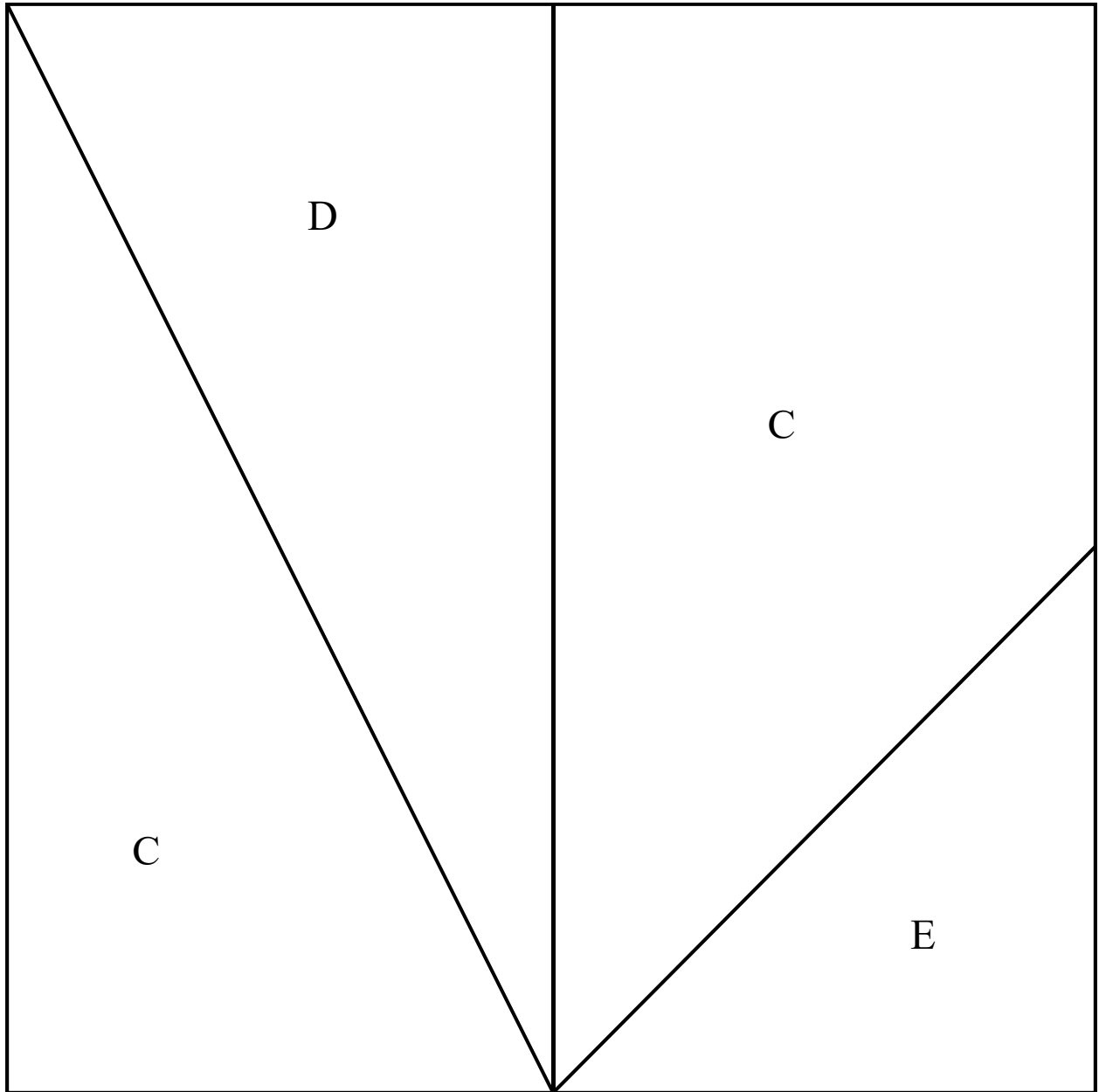
	<b>Model 1</b>		<b>Model 2</b>	
Intercept	107.29 ***	(0.62)	107.29 ***	(0.64)
Overall collaboration	-0.67	(0.64)	-0.67	(0.67)
Opponent defensive rating	-0.95	(0.65)	-0.95	(0.75)
Team diversity	0.69	(0.65)	0.69	(0.69)
Collaboration heterogeneity			0.01	(0.76)
$R^2$	.03		.09	

† =  $p < .10$ , \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .00$

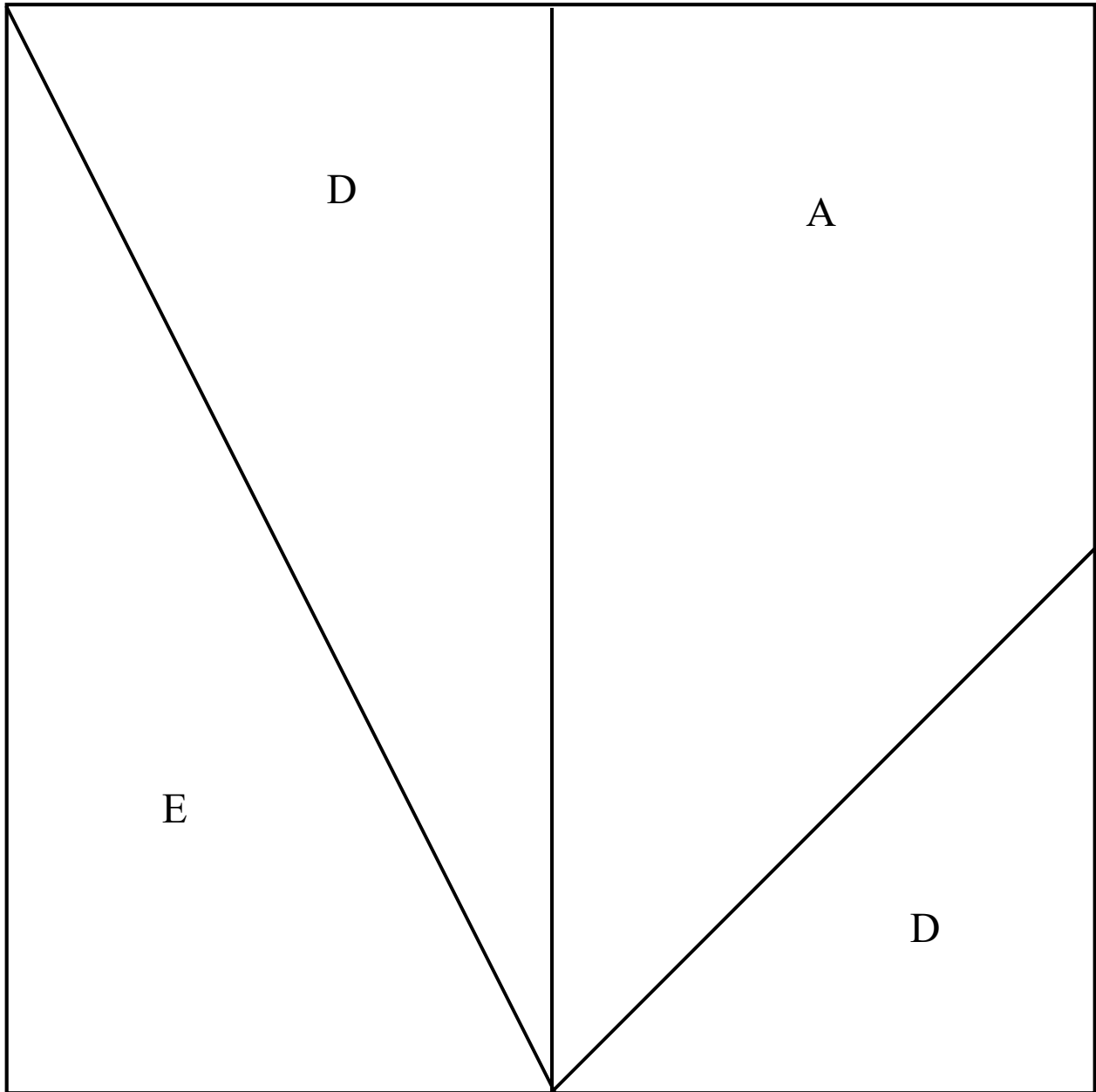
N = 30 teams

**APPENDIX 1: BROKEN SQUARES PUZZLES FOR STUDY 1**

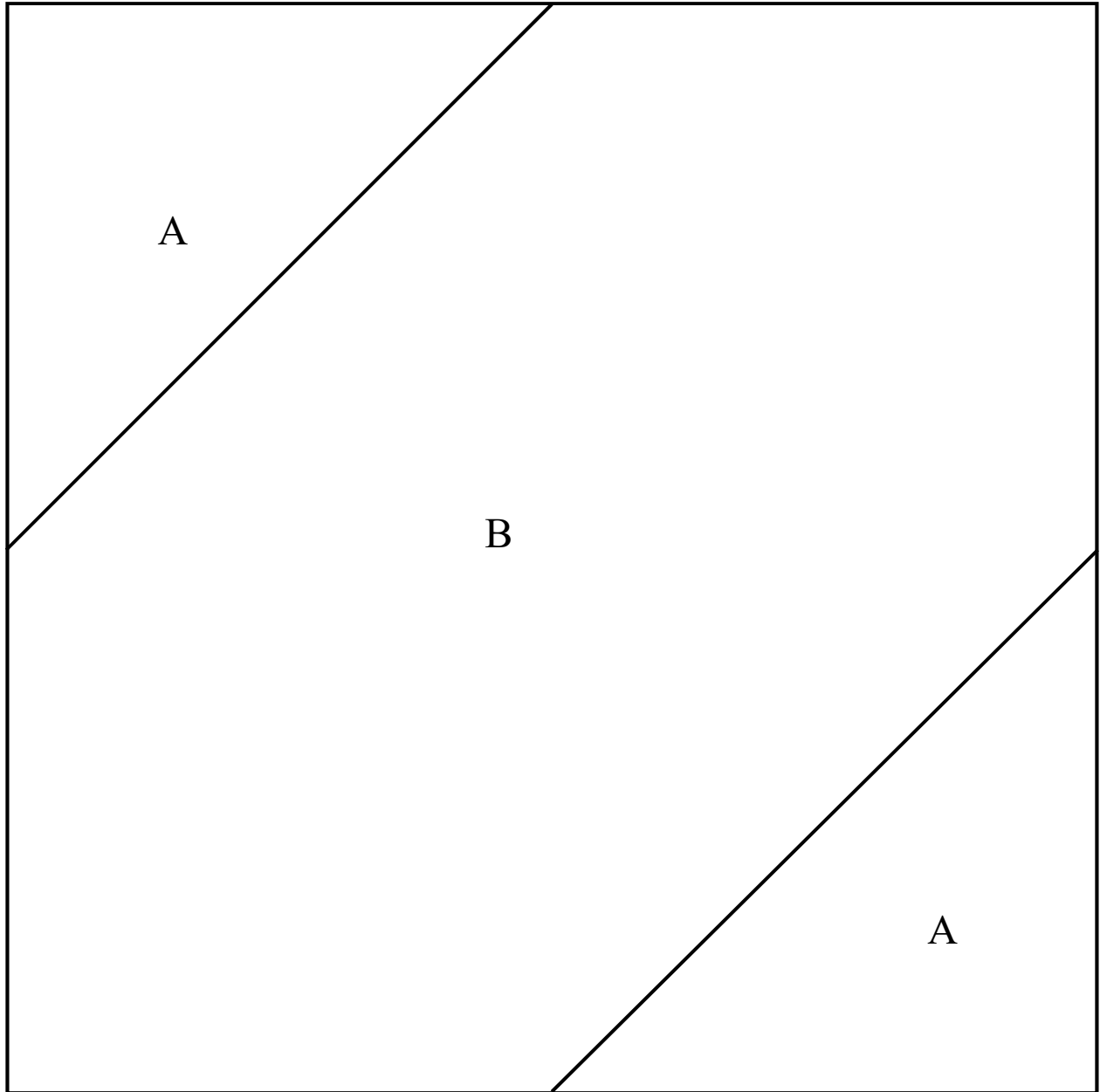
Round 1 Square 1



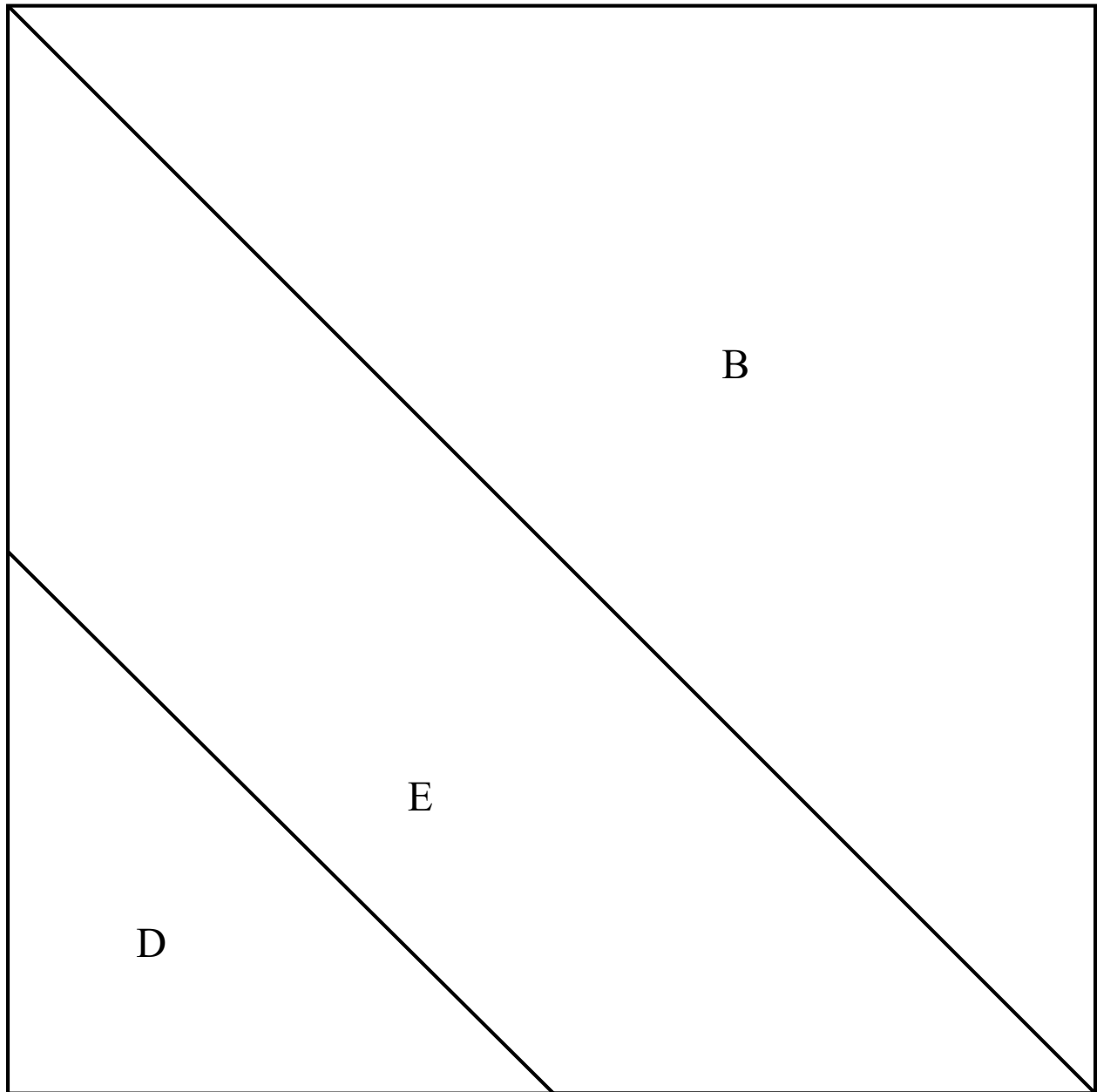
Round 1 Square 2



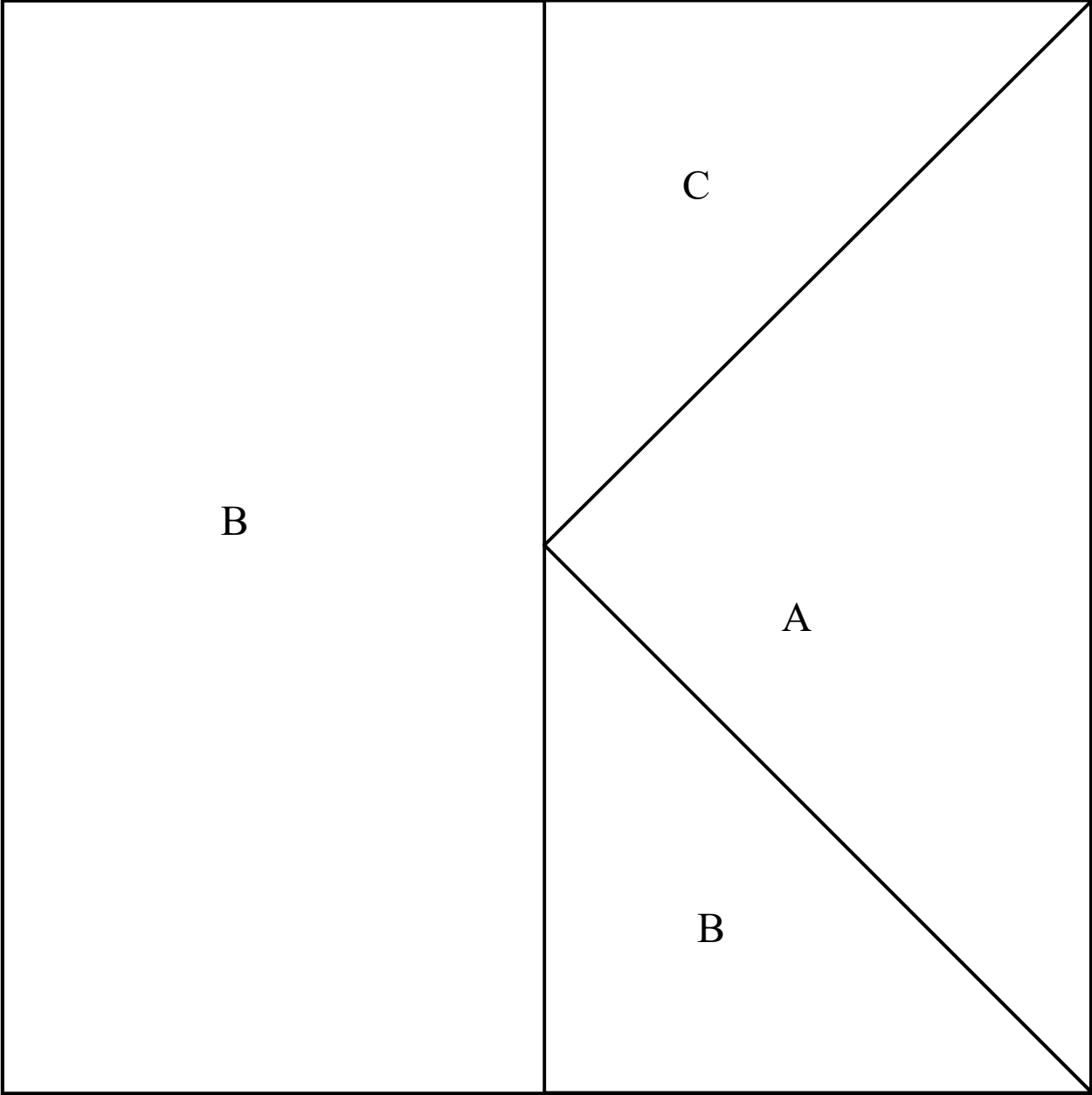
Round 1 Square 3



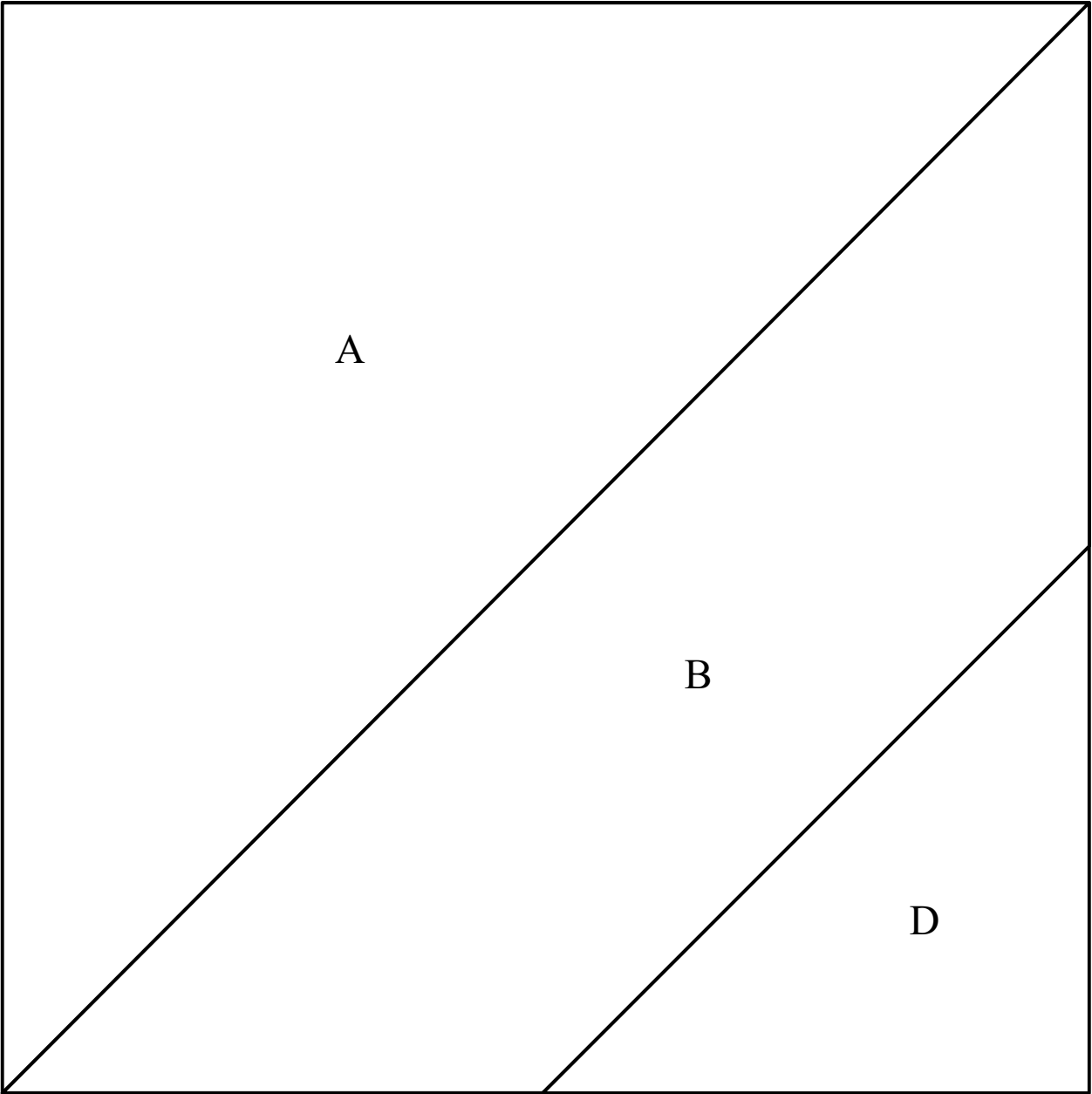
Round 1 Square 4



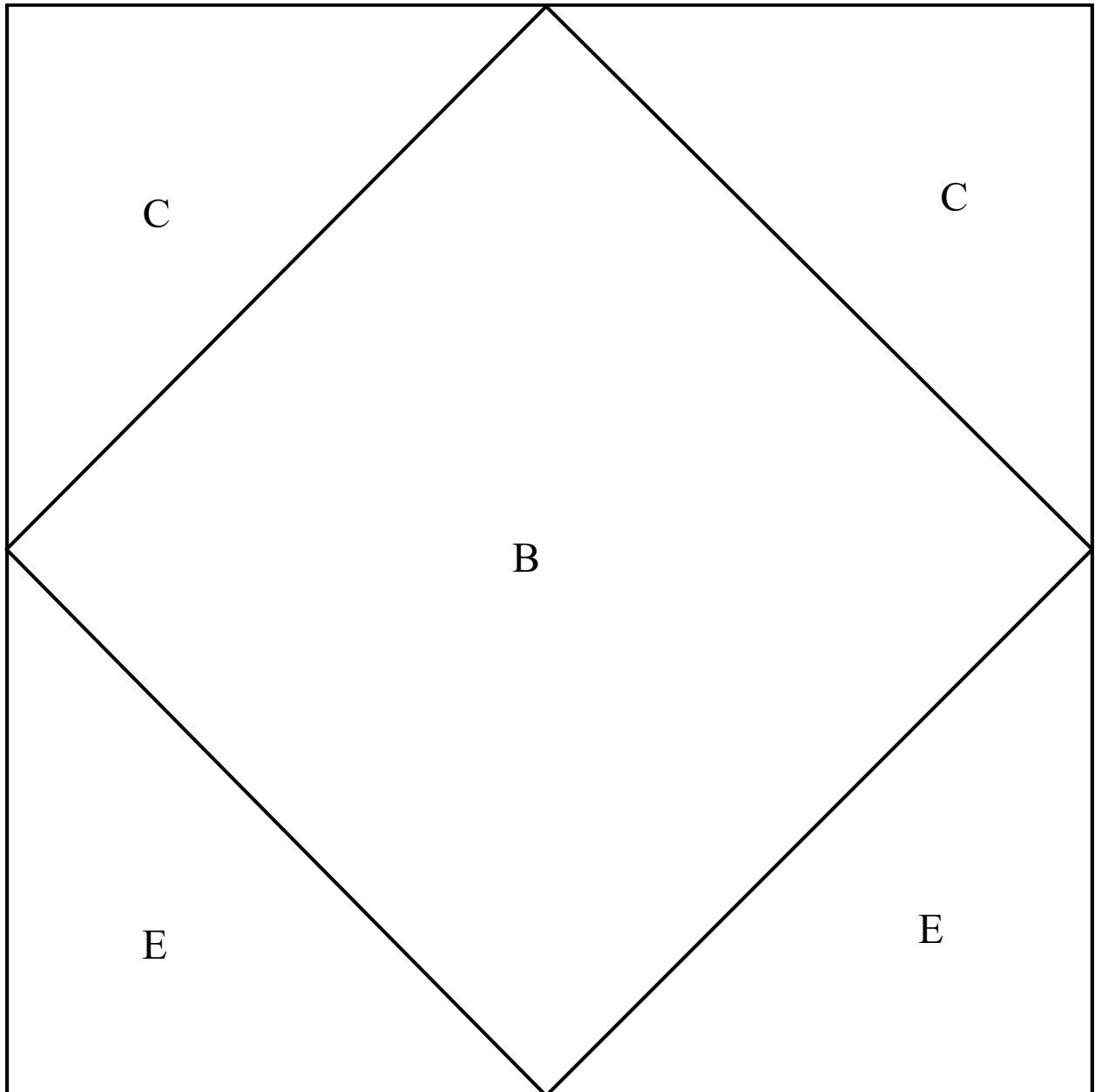
Round 1 Square 5



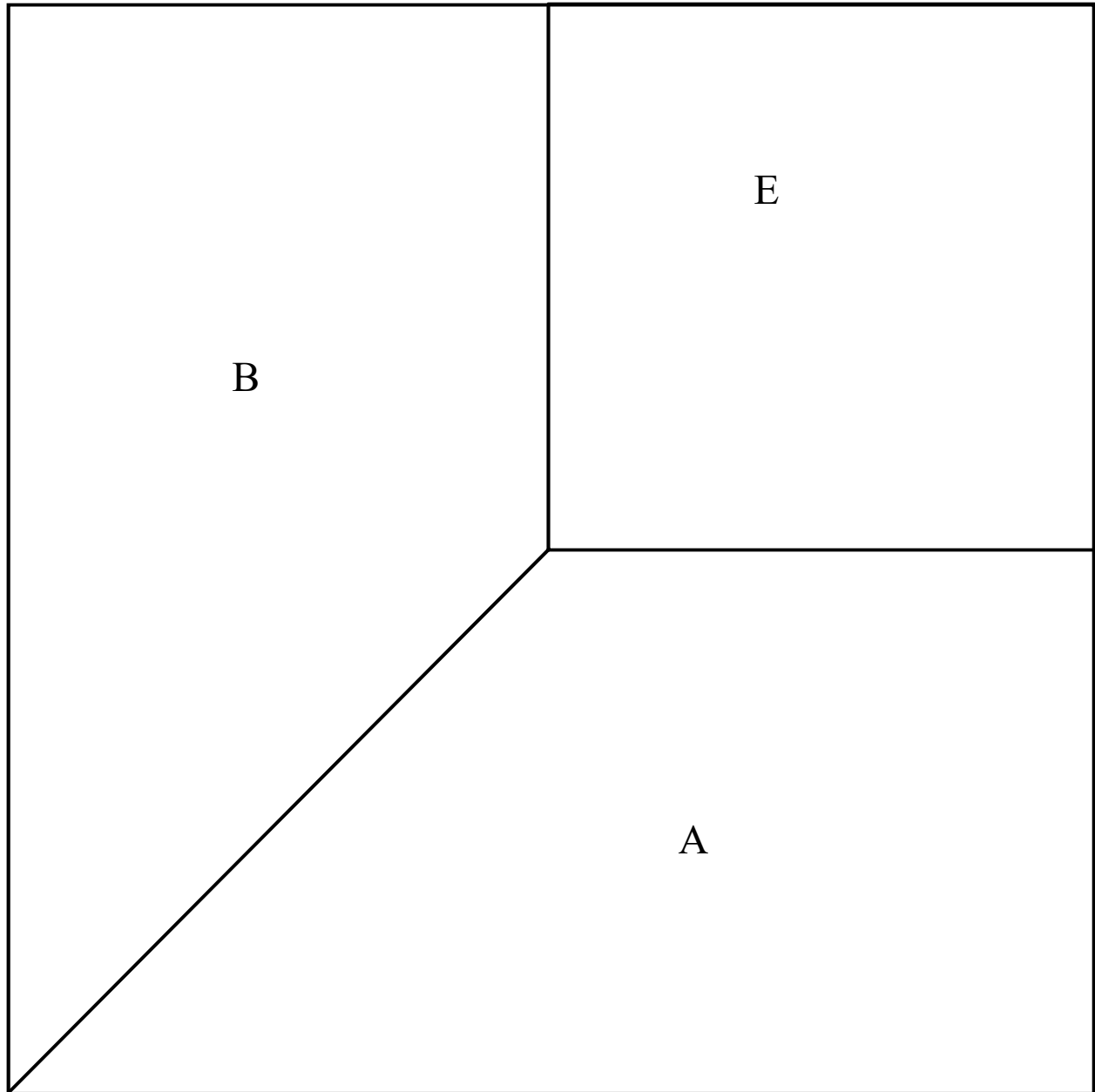
Round 2 Square 1



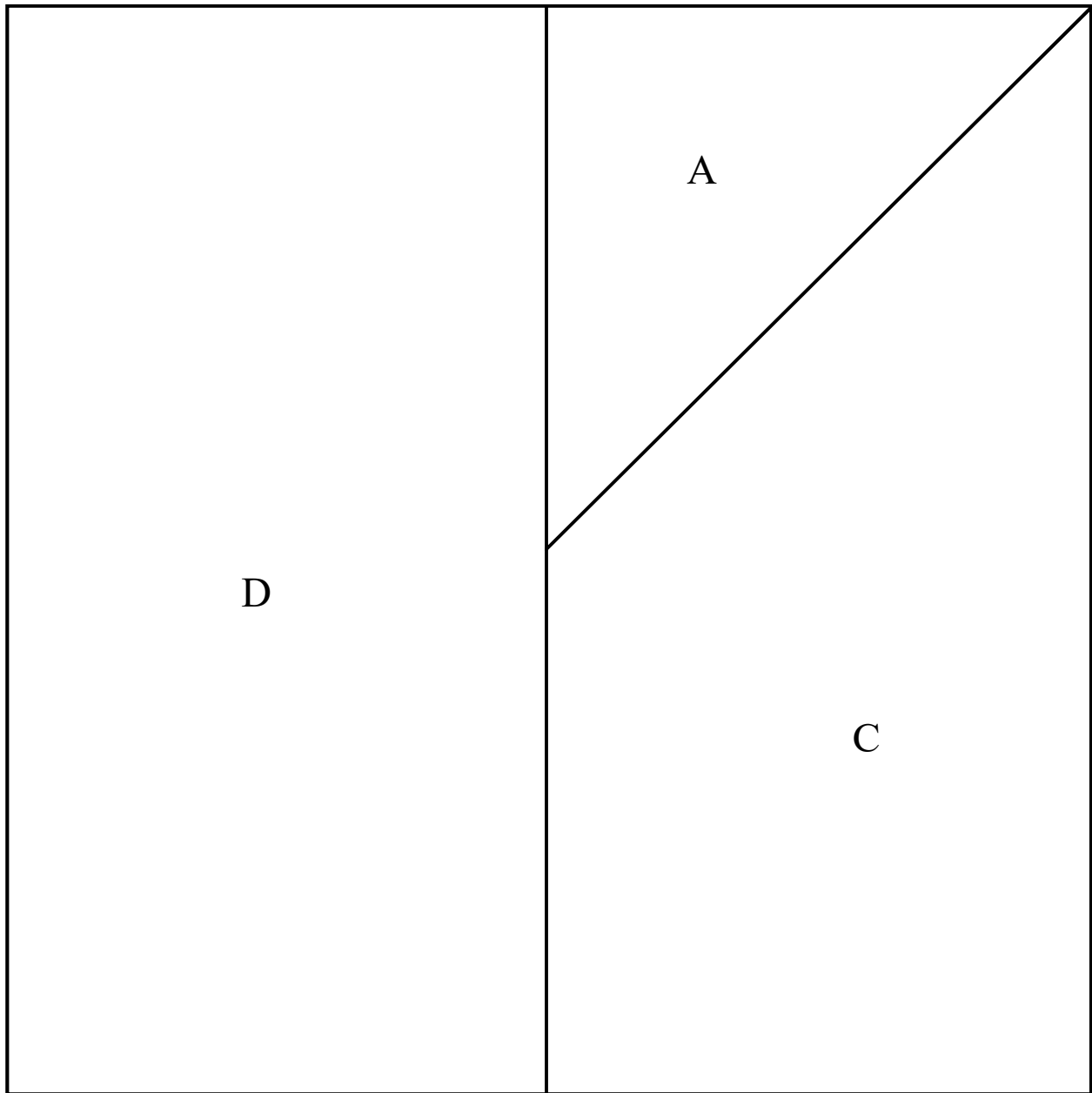
Round 2 Square 2



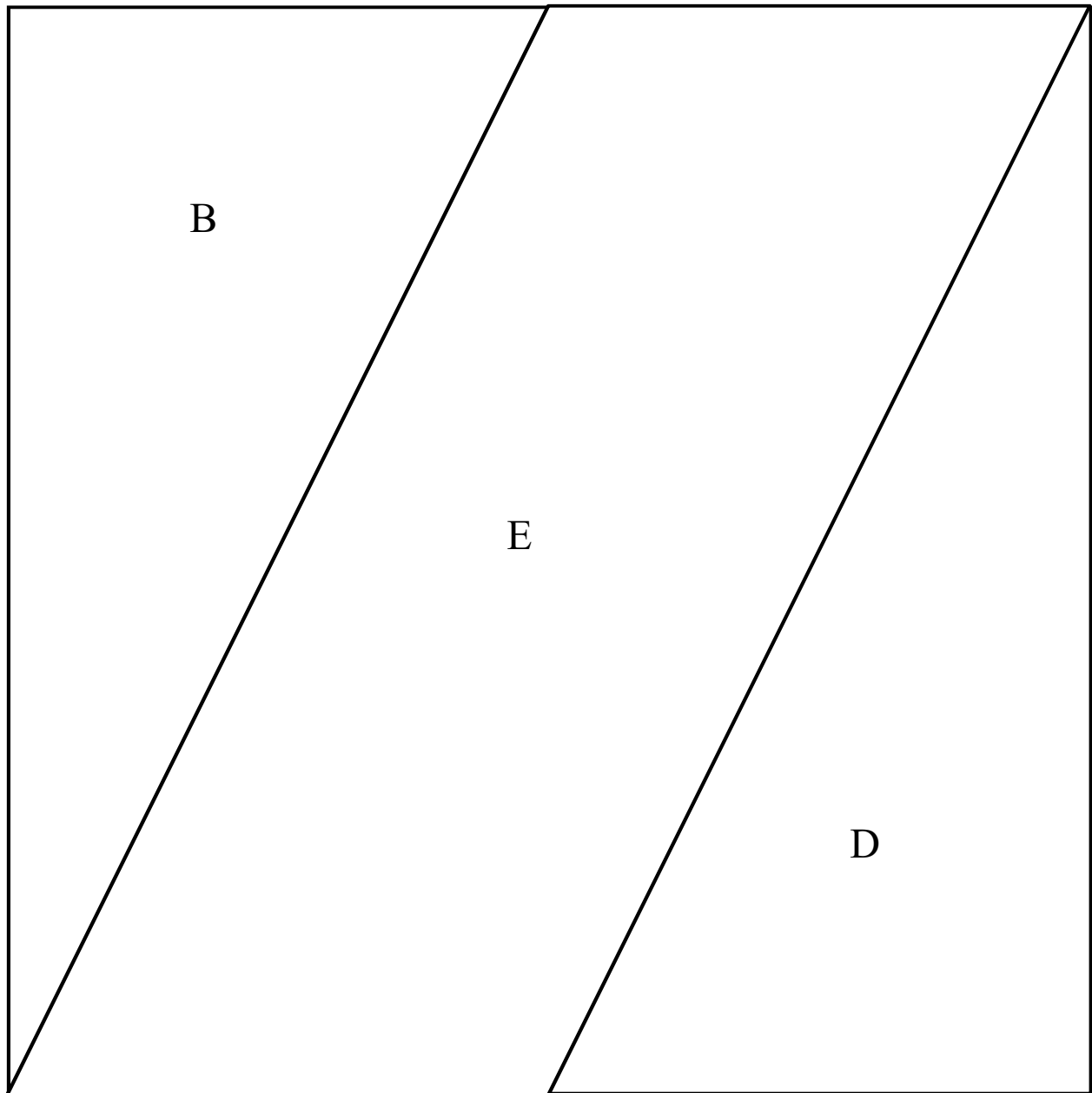
Round 2 Square 3



Round 2 Square 4



Round 2 Square 5



**APPENDIX 2: SAMPLE R CODE FOR NETWORK DATA ANALYSIS (STUDY 1)**

```

###
# Required packages
###

library(dplyr)
library(RSiena)

# this list filters which teams are in the active analysis
# exclude teams which do not converge

doThese <- c(100,
             # 101, #not in attempt 2
             102, #all white
             103,
             104,
             # 105, #no converge on subgroup, gender/crt or big5_0
interaction (worked a htird time) all white, a
             107, #no effect of gender
             108,
             110,
             # 111, #no gender effect, no converge on crt in 2
             112,
             113, #no gender effect
             114,
             115,
             116,
             # 118, #no converge on crt
             119,
             120, # won't converge on age or CRT
             # 122,
             # 123, #no gender effect, not in attempt 2
             127,
             128, #no gnder effect
             129,
             130,
             131,
             132,
             134,
             # 135, # no gender effect
             136,
             137, #no converge on CRT, big5_o or others
             138,
             # 139, # cno converge on CRT.2
             140,
             141, #wont converge on age
             142,
             143)

# loop to create data -----

###
# for attempt 1
###

```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```

for (i in 1:length(doThese)){
  print(paste0("team ",doThese[i],": i = ",i ))
  #convert edgelist
  temp <- as.data.frame(minuteEdgeList[minuteEdgeList$team == doThese[i] &
minuteEdgeList$attempt == 1,c("sender","receiver","passes","minute")]) #pull
one team
  size <- dataTeamTimes$TeamSize[dataTeamTimes$Team == doThese[i]] #team size
pulled from dataTeamTimes (wide), rather than derived fromtemp
  members <- if (size == 5) LETTERS[seq(1:5)] else LETTERS[seq(1:4)]
#derived from size rather than unique members (in case one person never
passed)
  waves <- seq(1:max(temp$minute)) #unique(temp$half) deriving number of
waves causes a problem if there are no passes in one wave

  #blank array
  temp.array <- array(0, dim=c(size,size,length(waves)),
dimnames=list(members,members,as.character(seq(1:length(waves)))))

  #fill array from edgelist
  for (j in 1:dim(temp)[1]) {
    row <- temp$sender[j]
    column <- temp$receiver[j]
    wave <- temp$minute[j]
    temp.array[row,column,wave] <- 1 #if I wanted weighted ties, change to
temp$passes[i]
  }

  passes <- sienaDependent(netarray = temp.array)
# assign(paste("dv",doThese[i],sep=""), tempdv) #make dv

#coCovar

temp <- dataQualtrics.scored[dataQualtrics.scored$team == doThese[i],
c("Q34",
  "team",
  "member",
  "big5_N",
  "big5_E",
  "big5_O",
  "big5_A",
  "big5_C",
  "posAff",
  "negAff",
  "divBelief",
  "XXXX",
  "XXCohesion",
  "teamConflict",
  "grpPrfSat",
  "grpDecSat",
  "gender",
  "age",
  "majorAcct",
  "majorEntre",
  "majorHRM",
  "majorFin",
  "majorIS",

```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
        "majorOM",
        "majorMKTG",
        "majorIB",
        "majorOther",
        "ethnicAfrAm",
        "ethnicAsian",
        "ethnicWhite",
        "ethnicHisp",
        "ethnicOther",
        "ethnicDecline",
        "CRT"
    )]

temp[is.na(temp)] <- NA #this might be necessary to get rid of NaN

temp <- temp[order(temp$member),] #because Siena doesn't use case numbers,
but order instead

###EDIT: 2017-02-21###

#Adding CRT
CRT <- coCovar(temp$CRT)

###END EDIT###

###EDIT: 2016-09-21###

temp$gender <- temp$gender - 1 #to make it a 1/0 rather than a 2/1. That
could be breaking the earlier version
temp$majorAcct[is.na(temp$majorAcct)] <- 0
temp$majorEntre[is.na(temp$majorEntre)] <- 0
temp$majorHRM[is.na(temp$majorHRM)] <- 0
temp$majorFin[is.na(temp$majorFin)] <- 0
temp$majorIS[is.na(temp$majorIS)] <- 0
temp$majorOM[is.na(temp$majorOM)] <- 0
temp$majorMKTG[is.na(temp$majorMKTG)] <- 0
temp$majorIB[is.na(temp$majorIB)] <- 0
temp$majorOther[is.na(temp$majorOther)] <- 0
temp$ethnicAfrAm[is.na(temp$ethnicAfrAm)] <- 0
temp$ethnicAsian[is.na(temp$ethnicAsian)] <- 0
temp$ethnicHisp[is.na(temp$ethnicHisp)] <- 0
temp$ethnicWhite[is.na(temp$ethnicWhite)] <- 0
temp$ethnicOther[is.na(temp$ethnicOther)] <- 0
temp$ethnicDecline[is.na(temp$ethnicDecline)] <- 0

majorAcct <- coCovar(temp$majorAcct)
majorEntre <- coCovar(temp$majorEntre)
majorHRM <- coCovar(temp$majorHRM)
majorFin <- coCovar(temp$majorFin)
majorIS <- coCovar(temp$majorIS)
majorOM <- coCovar(temp$majorOM)
majorMKTG <- coCovar(temp$majorMKTG)
majorIB <- coCovar(temp$majorIB)
majorOther <- coCovar(temp$majorOther)
ethnicAfrAm <- coCovar(temp$ethnicAfrAm)
ethnicAsian <- coCovar(temp$ethnicAsian)
ethnicWhite <- coCovar(temp$ethnicWhite)
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
ethnicHispanic <- coCovar(temp$ethnicHispanic)
ethnicOther <- coCovar(temp$ethnicOther)
ethnicDecline <- coCovar(temp$ethnicDecline)
divBelief <- coCovar(temp$divBelief)

# doesn't work because of multi-select, but can generally work to convert
dummies to factors
# factor(temp[,19:27]*%(1:8), labels = colnames(temp[,19:27]))

###END EDIT###

age <- coCovar(temp$age)
gender<- coCovar(temp$gender)
posAff<- coCovar(temp$posAff)
negAff<- coCovar(temp$negAff)
big5_N<- coCovar(temp$big5_N)
big5_E<- coCovar(temp$big5_E)
big5_O<- coCovar(temp$big5_O)
big5_A<- coCovar(temp$big5_A)
big5_C<- coCovar(temp$big5_C)

#coDyadCovar

temp <- dataQualtrics.scored[dataQualtrics.scored$team == doThese[i],
                             c("Q34",
                               "team",
                               "member",
                               "A_Relational",
                               "A_Compotence",
                               "B_Relational",
                               "B_Compotence",
                               "C_Relational",
                               "C_Compotence",
                               "D_Relational",
                               "D_Compotence",
                               "E_Relational",
                               "E_Compotence"
                             )]

temp[is.na(temp)] <- NA #this might be necessary to get rid of NaN

temp <- temp[order(temp$member),] #because Siena doesn't use case numbers,
but order instead

relational4 <-
c("A_Relational","B_Relational","C_Relational","D_Relational")
relational5 <-
c("A_Relational","B_Relational","C_Relational","D_Relational","E_Relational")
competence4 <-
c("A_Compotence","B_Compotence","C_Compotence","D_Compotence")
competence5 <-
c("A_Compotence","B_Compotence","C_Compotence","D_Compotence","E_Compotence")

compNames <- if (size == 5) competence5 else competence4
relNames <- if (size == 5) relational5 else relational4

r.mx <- as.matrix(cbind(temp[,relNames]))
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
dimnames(r.mx) <- list(members,members)
diag(r.mx) <- NA

relational <- coDyadCovar(r.mx)

c.mx <- as.matrix(cbind(temp[,compNames]))
dimnames(c.mx) <- list(members,members)
diag(c.mx) <- NA

competence <- coDyadCovar(c.mx)

fullObject <-
sienaDataCreate(passes,age,gender,ethnicAfrAm,ethnicAsian,ethnicWhite,ethnicH
isp,ethnicOther,ethnicDecline,majorAcct,majorEntre,majorHRM,majorFin,majorIS,
majorOM,majorMKTG,majorIB,majorOther,divBelief,posAff,negAff,big5_N,big5_E,bi
g5_O,big5_A,big5_C,relational,competence,CRT)

#to give it a unique name so it doesn't get overwritten
assign(paste("team",doThese[i],".byMin",sep=""), fullObject)

}

###
# for attempt 2
###

for (i in 1:length(doThese)){
  print(paste0("team ",doThese[i],": i = ",i ))
  #convert edgelists
  temp <- as.data.frame(minuteEdgeList[minuteEdgeList$team == doThese[i] &
minuteEdgeList$attempt == 2,c("sender","receiver","passes","minute")]) #pull
one team
  size <- dataTeamTimes$TeamSize[dataTeamTimes$Team == doThese[i]] #team size
pulled from dataTeamTimes (wide), rather than derived fromtemp
  members <- if (size == 5) LETTERS[seq(1:5)] else LETTERS[seq(1:4)]
#derived from size rather than unique members (in case one person never
passed)
  waves <- seq(1:max(temp$minute)) #unique(temp$half) deriving number of
waves causes a problem if there are no passes in one wave

  #blank array
  temp.array <- array(0, dim=c(size,size,length(waves)),
dimnames=list(members,members,as.character(seq(1:length(waves))))))

  #fill array from edgelist
  for (j in 1:dim(temp)[1]) {
    row <- temp$sender[j]
    column <- temp$receiver[j]
    wave <- temp$minute[j]
    temp.array[row,column,wave] <- 1 #if I wanted weighted ties, change to
temp$passes[i]
  }

  passes <- sienaDependent(netarray = temp.array)
  # assign(paste("dv",doThese[i],sep=""), tempdv) #make dv
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
#coCovar

temp <- dataQualtrics.scored[dataQualtrics.scored$team == doThese[i],
                             c("Q34",
                               "team",
                               "member",
                               "big5_N",
                               "big5_E",
                               "big5_O",
                               "big5_A",
                               "big5_C",
                               "posAff",
                               "negAff",
                               "divBelief",
                               "XXXX",
                               "XXCohesion",
                               "teamConflict",
                               "grpPrfSat",
                               "grpDecSat",
                               "gender",
                               "age",
                               "majorAcct",
                               "majorEntre",
                               "majorHRM",
                               "majorFin",
                               "majorIS",
                               "majorOM",
                               "majorMKTG",
                               "majorIB",
                               "majorOther",
                               "ethnicAfrAm",
                               "ethnicAsian",
                               "ethnicWhite",
                               "ethnicHisp",
                               "ethnicOther",
                               "ethnicDecline",
                               "CRT",
                               "subgroup"
                             )]

temp[is.na(temp)] <- NA #this might be necessary to get rid of NaN

temp <- temp[order(temp$member),] #because Siena doesn't use case numbers,
but order instead

# Tue May 08 21:57:27 2018 -----
# ADD subgroup
subgroup <- coCovar(temp$subgroup)

###EDIT: 2017-02-21###

#Adding CRT
CRT <- coCovar(temp$CRT)

###END EDIT###

###EDIT: 2016-09-21###
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
temp$gender <- temp$gender - 1 #to make it a 1/0 rather than a 2/1. That
could be breaking the earlier version
temp$majorAcct[is.na(temp$majorAcct)] <- 0
temp$majorEntre[is.na(temp$majorEntre)] <- 0
temp$majorHRM[is.na(temp$majorHRM)] <- 0
temp$majorFin[is.na(temp$majorFin)] <- 0
temp$majorIS[is.na(temp$majorIS)] <- 0
temp$majorOM[is.na(temp$majorOM)] <- 0
temp$majorMKTG[is.na(temp$majorMKTG)] <- 0
temp$majorIB[is.na(temp$majorIB)] <- 0
temp$majorOther[is.na(temp$majorOther)] <- 0
temp$ethnicAfrAm[is.na(temp$ethnicAfrAm)] <- 0
temp$ethnicAsian[is.na(temp$ethnicAsian)] <- 0
temp$ethnicHisp[is.na(temp$ethnicHisp)] <- 0
temp$ethnicWhite[is.na(temp$ethnicWhite)] <- 0
temp$ethnicOther[is.na(temp$ethnicOther)] <- 0
temp$ethnicDecline[is.na(temp$ethnicDecline)] <- 0

majorAcct <- coCovar(temp$majorAcct)
majorEntre <- coCovar(temp$majorEntre)
majorHRM <- coCovar(temp$majorHRM)
majorFin <- coCovar(temp$majorFin)
majorIS <- coCovar(temp$majorIS)
majorOM <- coCovar(temp$majorOM)
majorMKTG <- coCovar(temp$majorMKTG)
majorIB <- coCovar(temp$majorIB)
majorOther <- coCovar(temp$majorOther)
ethnicAfrAm <- coCovar(temp$ethnicAfrAm)
ethnicAsian <- coCovar(temp$ethnicAsian)
ethnicWhite <- coCovar(temp$ethnicWhite)
ethnicHisp <- coCovar(temp$ethnicHisp)
ethnicOther <- coCovar(temp$ethnicOther)
ethnicDecline <- coCovar(temp$ethnicDecline)
divBelief <- coCovar(temp$divBelief)

# doesn't work because of multi-select, but can generally work to convert
dummies to factors
# factor(temp[,19:27]%*(1:8), labels = colnames(temp[,19:27]))

###END EDIT###

age <- coCovar(temp$age)
gender<- coCovar(temp$gender)
posAff<- coCovar(temp$posAff)
negAff<- coCovar(temp$negAff)
big5_N<- coCovar(temp$big5_N)
big5_E<- coCovar(temp$big5_E)
big5_O<- coCovar(temp$big5_O)
big5_A<- coCovar(temp$big5_A)
big5_C<- coCovar(temp$big5_C)

#coDyadCovar

temp <- dataQualtrics.scored[dataQualtrics.scored$team == doThese[i],
                           c("Q34",
                             "team",
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```

        "member",
        "A_Relational",
        "A_Compotence",
        "B_Relational",
        "B_Compotence",
        "C_Relational",
        "C_Compotence",
        "D_Relational",
        "D_Compotence",
        "E_Relational",
        "E_Compotence"
    )]

    temp[is.na(temp)] <- NA #this might be necessary to get rid of NaN

    temp <- temp[order(temp$member),] #because Siena doesn't use case numbers,
    but order instead

    relational4 <-
    c("A_Relational","B_Relational","C_Relational","D_Relational")
    relational5 <-
    c("A_Relational","B_Relational","C_Relational","D_Relational","E_Relational")
    competence4 <-
    c("A_Compotence","B_Compotence","C_Compotence","D_Compotence")
    competence5 <-
    c("A_Compotence","B_Compotence","C_Compotence","D_Compotence","E_Compotence")

    compNames <- if (size == 5) competence5 else competence4
    relNames <- if (size == 5) relational5 else relational4

    r.mx <- as.matrix(cbind(temp[,relNames]))
    dimnames(r.mx) <- list(members,members)
    diag(r.mx) <- NA

    relational <- coDyadCovar(r.mx)

    c.mx <- as.matrix(cbind(temp[,compNames]))
    dimnames(c.mx) <- list(members,members)
    diag(c.mx) <- NA

    competence <- coDyadCovar(c.mx)

    fullObject <- sienaDataCreate(passes,
    subgroup,age,gender,ethnicAfrAm,ethnicAsian,ethnicWhite,ethnicHisp,ethnicOthe
    r,ethnicDecline,majorAcct,majorEntre,majorHRM,majorFin,majorIS,majorOM,majorM
    KTG,majorIB,majorOther,divBelief,posAff,negAff,big5_N,big5_E,big5_O,big5_A,bi
    g5_C,relational,competence,CRT)

    #to give it a unique name so it doesn't get overwritten
    assign(paste("team",doThese[i],".byMin.Attempt2",sep=""), fullObject)
}

# analysis -----

```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
#create team level models

suffix <- ".sameSubGroup.a2"

# i = 26
#TIME 1
for (i in 1:length(doThese)){
  print(paste("group ",i,": team",doThese[i],".byMin",sep=""))
  X <- get(paste0("team",doThese[i],".byMin"))
  eff <- getEffects(X)
  eff <- includeEffects(eff, sameX, interaction1 = "gender")
  algo <- sienaAlgorithmCreate()
  model <- siena07(algo, data = X, effects = eff)
  assign(paste("team",doThese[i],suffix,sep=""), model)
}

#TIME 2
for (i in 25:length(doThese)){
  print(paste("group ",i,": team",doThese[i],".byMin.Attempt2",sep=""))
  X <- get(paste0("team",doThese[i],".byMin.Attempt2"))
  eff <- getEffects(X)
  eff <- includeEffects(eff, sameX, interaction1 = "subgroup")
  algo <- sienaAlgorithmCreate()
  model <- siena07(algo, data = X, effects = eff)
  assign(paste("team",doThese[i],suffix,sep=""), model)
}

####
# after creating models and excluding teams, run doThese again and then run
code below for pasting into formula below
####
for (i in 1:length(doThese)){
  print(as.name(paste0("team",doThese[i],suffix)))
}

meta.sameSubGroup.a2 <- siena08(team100.sameSubGroup.a2,
                                team102.sameSubGroup.a2,
                                team103.sameSubGroup.a2,
                                team104.sameSubGroup.a2,
                                team107.sameSubGroup.a2,
                                team108.sameSubGroup.a2,
                                team110.sameSubGroup.a2,
                                team112.sameSubGroup.a2,
                                team113.sameSubGroup.a2,
                                team114.sameSubGroup.a2,
                                team115.sameSubGroup.a2,
                                team116.sameSubGroup.a2,
                                team119.sameSubGroup.a2,
                                team120.sameSubGroup.a2,
                                team127.sameSubGroup.a2,
                                team128.sameSubGroup.a2,
                                team129.sameSubGroup.a2,
                                team130.sameSubGroup.a2,
                                team131.sameSubGroup.a2,
                                team132.sameSubGroup.a2,
                                team134.sameSubGroup.a2,
                                team136.sameSubGroup.a2,
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
meta.sameSubGroup.a2  
team137.sameSubGroup.a2,  
team138.sameSubGroup.a2,  
team140.sameSubGroup.a2,  
team141.sameSubGroup.a2,  
team142.sameSubGroup.a2,  
team143.sameSubGroup.a2)
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

### APPENDIX 3: SAMPLE R CODE FOR TEAM DATA ANALYSIS (STUDY 2)

```
library(lmtest) #for Breusch-Pagan Test

# Sample characteristics -----

table(dataQualtrics.scored$team) #44 teams, 194 subjects
mean(dataQualtrics.scored$gender) #1.56 (1 = female 44%, 2 = male 56%)
mean(dataQualtrics.scored$age, na.rm = TRUE) #21.35
table(dataQualtrics.scored$ethnicWhite) #113 / 194 = 58.24%
table(dataQualtrics.scored$ethnicAsian) #64 / 194 = 32.99%

# Variance Hypothesis -----

library(olsrr)

#gender
tempModel <- lm(Time.2 ~ blau, teamCoeffs)
bptest(tempModel) #BP = 3.7251, df = 1, p-value = 0.0536
#this uses the Kroneker 1981 studentized version

#ethnicity
tempModel <- lm(Time.2 ~ ethnicityBlau, teamCoeffs)
summary(tempModel)
bptest(tempModel) #BP = 0.80681, df = 1, p-value = 0.3691

#information
tempModel <- lm(Time.2 ~ conditionBlau, teamCoeffs)
summary(tempModel)
bptest(tempModel) #BP = 2.4551, df = 1, p-value = 0.1171

# Heterogeneity - Performance Hypotheses -----

model0 <- lm(Time.2 ~ passesAttempt2, data = teamCoeffs)
summary(model0)

model2 <- lm(Time.2 ~ scale(passesAttempt2) + scale(blau), data = teamCoeffs)
summary(model2)

model3 <- lm(Time.2 ~ scale(passesAttempt2) + scale(blau) + scale(-
sameGender.a2), data = teamCoeffs)
summary(model3)

model7 <- lm(Time.2 ~ scale(passesAttempt2) + scale(ethnicityBlau), data =
teamCoeffs)
summary(model7)
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
model8 <- lm(Time.2 ~ scale(passesAttempt2) + scale(ethnicityBlau) + scale(-
WhiteSame.a2), data = teamCoeffs)
summary(model8)

model9 <- lm(Time.2 ~ scale(passesAttempt2) + scale(ethnicityBlau) +
scale(AsianSame.a2.rev), data = teamCoeffs)
summary(model9)
#white and asian correlated at .93

#subgroupsame.a2 -- limit to only disparity or separation
model11 <- lm(Time.2 ~ scale(passesAttempt2) + scale(conditionCV), data =
teamCoeffs[teamCoeffs$Diversity == "Separation" | teamCoeffs$Diversity ==
"Disparity",])
summary(model11)
model12 <- lm(Time.2 ~ scale(passesAttempt2) + scale(conditionCV) + scale(-
sameSubgroup.a2), data = teamCoeffs[teamCoeffs$Diversity == "Separation" |
teamCoeffs$Diversity == "Disparity",])
summary(model12)
model13 <- lm(Time.2 ~ scale(passesAttempt2) + scale(conditionBlau), data =
teamCoeffs[teamCoeffs$Diversity == "Separation" | teamCoeffs$Diversity ==
"Disparity",])
summary(model13)
model14 <- lm(Time.2 ~ scale(passesAttempt2) + scale(conditionBlau) + scale(-
sameSubgroup.a2), data = teamCoeffs[teamCoeffs$Diversity == "Separation" |
teamCoeffs$Diversity == "Disparity",])
summary(model14)
```

## APPENDIX 4: SAMPLE R CODE FOR NBA DATA COLLECTION

```

###
# Required packages
###

library(httr)
library(RSelenium)
library(plyr)

# Generate dataset to prepare for data scraping-----

date.df <- as.data.frame(matrix(nrow=0,ncol=2))

for (i in 1:length(gamenums1314[,1])){
  gamenum <- gamenums1314[i,]
  gameURL <- paste("http://stats.nba.com/game/#!/00",gamenum,"/",sep="")
  checkForServer()
  startServer()
  remDr <- remoteDriver$new()
  remDr$open()
  remDr$navigate(gameURL)
  Sys.sleep(20)
  doc.loop <- htmlParse(remDr$getPageSource()[[1]])
  root.loop <- xmlRoot(doc.loop)
  date <- as.character(xpathSApply(root.loop,"//*[@class='game-date ng-
binding']",xmlValue)) #that's it
  row <- cbind(gamenum,date)
  date.df <- rbind.data.frame(date.df,row)
  remDr$close()
}

names(date.df) <- c("game","date")

date.df[date.df$date == "",] #missed one

date.df[date.df$date == "", "date"] <- "Jan 10, 2014"

###
#pull existing advanced stats data
###

gamedata <- read.csv("nbaadvstats1314.csv", stringsAsFactors = FALSE)

###
# merge game dates in
###

temp <- merge(gamedata,date.df)
gamedata <- temp
rm(temp)

###
#pull player ID file
###

```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
playerID <- read.csv("playerIDs.csv", header=F, stringsAsFactors = FALSE)
names(playerID) <- c("name","teamMain","statsURL","extra","playerID")

#problem with "lou willams" "louis williams"

playerID[playerID$name == "Lou Williams","name"] <- "Louis Williams"

###
#merge player IDs in
###

gamedata[gamedata$name == "Tony Mitchell" & gamedata$team == "DET", "name"]
<- "Tony Mitchell DET"
gamedata[gamedata$name == "Tony Mitchell" & gamedata$team == "MIL", "name"]
<- "Tony Mitchell MIL"

playerID[playerID$name == "Tony Mitchell" & playerID$teamMain == "DET",] <-
"Tony Mitchell DET"
playerID[playerID$name == "Tony Mitchell" & playerID$teamMain == "MIL",] <-
"Tony Mitchell MIL"

temp <- merge(gamedata,playerID,by = "name", all.x=TRUE) #trying again, got
it
gamedata <- temp
rm(temp)

###
#convert date to the right format
###

gamedata$date <- as.character(gamedata$date)
gamedata$date.posix <- strptime(gamedata$date, format = "%b %e, %Y")
gamedata$month <- gamedata$date.posix$mon + 1
gamedata[gamedata$month < 10,"month"] <- paste("0",gamedata[gamedata$month <
10,"month"],sep="")
gamedata$day <- gamedata$date.posix$mday
gamedata[gamedata$day < 10,"day"] <- paste("0",gamedata[gamedata$day <
10,"day"],sep="")
gamedata$year <- gamedata$date.posix$year + 1900

###
# Variables for data scraping
###

playergameID <- subset(gamedata,select =
c("name","playerID","statsURL","team","game","date","month","day","year"))

# data scraping loop -----

#to make the URL

passto.df <- as.data.frame(matrix(nrow=0,ncol=17))

for (i in 1:25536) {
  tryCatch({
    playerID <- playergameID$playerID[i]
    month <- playergameID$month[i]
```

## CHAPTER 3: HETEROGENEOUS COLLABORATION AND TEAM PERFORMANCE

```
year <- playergameID$year[i]
day <-playergameID$day[i]
URL <-
paste("http://stats.nba.com/player/#!/",playerID,"/tracking/passes/?Season=20
13-14&SeasonType=Regular%20Season&PerMode=Totals&DateFrom=",month,"-",day,"-
",year,"&DateTo=",month,"-",day,"-",year,sep="")

#to grab the URL

checkForServer()
startServer()
remDr <- remoteDriver$new()
remDr$open()
print(i)
remDr$navigate(URL)
Sys.sleep(5)
raw <- remDr$getPageSource()[[1]]
doc <- htmlParse(raw)
# doc2 <- htmlTreeParse(raw)
tables <- readHTMLTable(doc,stringsAsFactors=FALSE)
# links <- xpathSApply(doc, "//a/@href")
links <- xpathSApply(doc, "//a/@href")
targets <- xpathSApply(doc, "//a")
remDr$close()

passto <- tables[[3]]
# passfrom <- tables[[4]]

colnames(passto)[1] <- "passTo"
# colnames(passfrom)[1] <- "passFrom"
colnames(passto)[8] <- "FGPct"
# colnames(passfrom)[8] <- "FGPct"
colnames(passto)[11] <- "2FGPct"
# colnames(passfrom)[11] <- "2FGPct"
colnames(passto)[14] <- "3FGPct"
# colnames(passfrom)[14] <- "3FGPct"

passto$passer <- playerID
passto$team <- playergameID$team[i]
passto$game <- playergameID$game[i]

passto.df <- rbind(passto.df,passto)
}, error=function(e){})
}

write.csv(x = passto.df, file = "passingdata.csv")
```