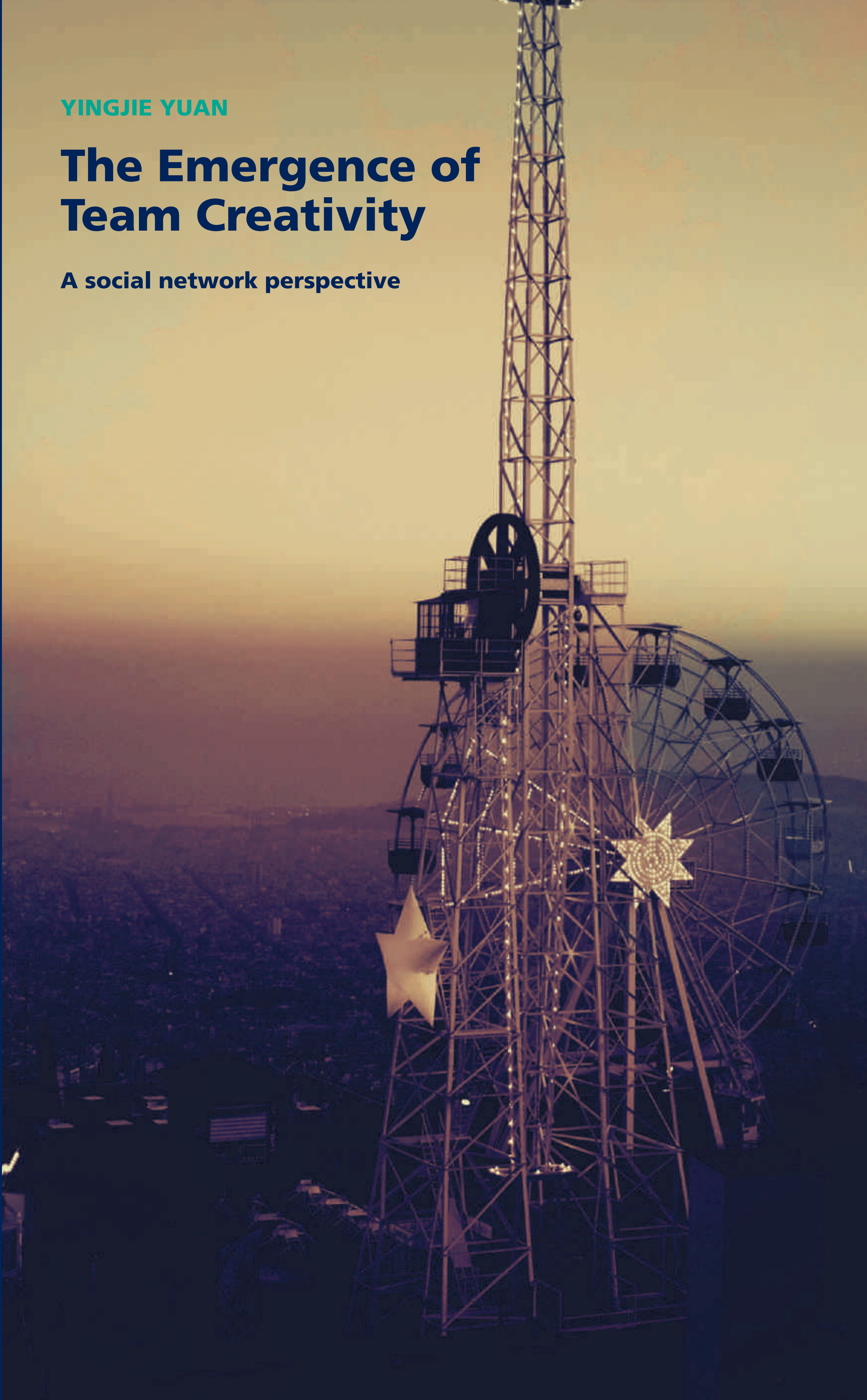
YINGJIE YUAN

The Emergence of Team Creativity

A social network perspective



The Emergence of Team Creativity:

A social network perspective

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A social network perspective

Het ontstaan van team creativiteit:
Een sociaal netwerk perspectief

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Chapter 1 General Introduction

"As a species, we build on the collective creativity not just of those in our own time but of those who have come before us. Marx long ago said that what made the proletariat a universal class was the collaborative nature of physical labor. But what sets us apart from all other species is our collective creativity, something that is innate in each of us and shared by every one of us."

--Richard Florida, a quote from The Rise of the Creative Class

The need for creativity is bold in this post-industrial epoch. Our lives, either economic or social, valorize materialism and consumption, which label individuals with mass production and branded characteristics of merchandise. Economically, in virtually every industry, from rocket science to fashion industry, creativity is the evergreen advantage for companies to stand out in the fierce competition. In social lives, our identities are much shaped by our purchase. We live in housing blocks, wear identical clothes from mass production, and use almost the same electronic goods from top to toe. The urge of unique identifiers calls not only for personal expressions via novel and customized consumptions but also for the development of our potential and individuality through work and social activities. Creativity ushers in a new era of prosperity, sustainability, and self-actualization.

In the business world, creativity is more than ever a top priority—creativity sells. Managers, venture investors, entrepreneurs, and analysts—all fish for the next iPhone, the next Tesla, the next Uber, the next Pokémon Go, or any other novel project or proposal that might revolutionize industrial paradigms, raise public expectations, and eventually bring in profit and prestige. Consequently, for employees, creativity means jobs, competitiveness, stability, financial income and prosperity. In this information era, where routine work and traditional skills can easily be automated or outsourced, creative skills become the real, indispensable human capital. For instance, till 2014, creative employees in science, technology, media, culture and the arts have made up one-third to nearly half of the workforce all over the world (Florida, 2014). Even when US unemployment rate topped 10%, creative employees hold less than half of the unemployed (Florida, 2014). Creative employment fuels economic development and is valued and nurtured more than ever before.

Given such strong appeal, it is all the more poignant, then, that our popular understanding of creativity is based on a widespread myth—the myth that creativity thrives primarily in individuals. Widespread is the notion of lone “creative genius” like da Vinci, Cavendish, and Freud, who flourish in solitude. Yet, as put by Kelley and Littman (2007), “even the most legendary individual inventor is often a team in disguise”. Thomas Edison patented hundreds of inventions, but they were actually collective works of Edison and his fourteen-man engineering team. Quentin Tarantino, the acclaimed director, could not have accomplished his signature style without his film crews. The same is true for innovative entrepreneurs such as Mark Zuckerberg (co-founder of Facebook), Elon Musk (founder of Tesla), Luis van Ahn (creator of Duolingo), and John Hanke (founder of Pokémon Go).

The increasing attention to creativity as a collective endeavor coincides with the pervading trend of teamwork in business in the last decades (Wuchty, Jones, & Uzzi, 2007a). The power of teamwork was first recognized in the 1960s when Japanese enterprises rose as a global economic power and impressed Western firms with their unparalleled management styles revolving around work teams. By the 1980s, the value of teamwork and team-based processes was established among behavioral scientists and practitioners in both public and private sectors. Nowadays, as a response to the turbulent business environment (e.g., technological advancement, international competition, and rapidly changing markets), organizations are pushed to apply teamwork strategies to integrate resources and opportunities across industries and geographic borders and to develop novel products, customer services, and operation processes. The question really is: how to foster creativity in work teams.

The Emergence of Team Creativity: A Brief Review

In order to understand the emergence of team creativity, I will define creativity in organizational contexts from the outset. Throughout this dissertation, creativity is defined from the problem-solving perspective as novel and useful solutions to organizational issues (e.g., Amabile, 1988b; Perry-Smith and Shalley, 2003; Hargadon and Bechky, 2006; Shalley and Zhou, 2008). This definition derives from creativity research in organizational contexts and therefore differs from the one used in the brainstorming literature, where creativity is conceptualized as the fluency or quantity rather than the value or quality of generated ideas (Brown, Tumeo, Larey, & Paulus, 1998; Paulus, 2000). Moreover, in organizational contexts, creative solutions may be expressed in both tangible and intangible forms such as products, services, processes, strategies, and ideas (Oldham & Cummings, 1996; Woodman, Sawyer, & Griffin, 1993). Following this definition, individual creativity in organizations reflects the propensity to develop novel and useful solutions by virtue of individual creativity-relevant skills, domain-relevant expertise, and intrinsic task motivation in accordance to Amabile's (1988a) componential model of creativity (Amabile, 1983; Staw, 2009; van Knippenberg & Hirst, 2015). Team creativity, on the other hand, is defined as the generation of creative solutions among a group of people working interdependently on one team task (Shalley & Zhou, 2008; Woodman et al., 1993).

Although decades of research have greatly advanced our understanding of how creativity at the individual level could be facilitated or inhibited by two major sets of factors— intrapersonal resources and contextual influences (e.g., Farmer, Tierney, & Kung-Mcintyre, 2003; Perry-Smith & Shalley, 2003; van Knippenberg & Hirst, 2015; Zhang & Bartol, 2010) —our understanding of how team creativity emerges from individual and contextual inputs is disproportionately limited. So far, some scholars have extended theories about individual creativity to the team level and identified some individual characteristics and contextual triggers that foster the generation of team creativity (e.g., Baer, Oldham, Jacobsohn, & Hollingshead, 2008; Gong, Kim, Lee, & Zhu, 2013; van Kleef, Anastasopoulou, & Nijstad, 2010). Yet such endeavors, from the overarching view of team functioning, are rather scarce and fragmented.

Small group research in the past decades has greatly contributed to our understanding of team phenomena in general. Several conceptual models have been proposed to understand how team functions, from the original IPO model (Input-Process-Output model, Hackman, 1987; Steiner, 1972), through the later version of IMOI model (Input-Mediator-Output-Input model, Ilgen, Hollenbeck, Johnson, & Jundt, 2005), to the latest more temporal and dynamic team models (e.g., Mathieu, Tannenbaum, Donsbach, & Alliger, 2014). All these models capture one fundamental logic—both individual and environmental resources enter into team processes in the various forms of configurations, and then convert into the final team outputs during the collective processing. In this overarching logic that applies to all team constructs including team creativity, three basic elements are identified: a) team inputs of individual dispositions and contextual influences;

b) collective processes that attend to and synergize disposable inputs; and c) team structures in which team inputs are configured and team processes are embedded. This overarching framework, therefore, presents a conceptual model to understand how team creativity emerges from the joint impacts of team composition, team process, and team structure. Below I will briefly review team creativity research from these three fundamental elements.

Oversimplified Team Composition Models in Team Creativity Research

Although all the social factors that enter in team processes for creative success can in a broad sense be counted as creative inputs, individual dispositions are the real starting point of understanding team creativity. The tradition of examining individual dispositions can be traced back to Amabile's componential theory that proposes the determining roles of three individual dispositions—creative abilities, task-related skills, and motivations (Amabile, 1983, 1988a). The logic of individual differences as creative inputs is that the source of team creativity lies in individuals' creative ideas and their team's capabilities to recognize and utilize such ideas, both of which derive from individual members' knowledge repository, cognitive abilities, personalities (Baer et al., 2008), and psychological states such as epistemic motivation and positive mood (e.g., individual creative abilities, Taggar, 2002; demographic factors, Shin and Zhou, 2007; motivational states, van Kleef, Anastasopoulou, and Nijstad, 2010; affects, Tsai et al., 2012).

In the meantime, how dispositional resources get configured in team activities seems equally important as, if not more important than, the dispositional resources *per se*. For instance, does a pharmaceutical R&D team tasked with developing new solutions for diabetes fall back on continuous brainstorming among all members, or select a few ingenious ideas to develop into team solutions? Different composition models reflect distinct strategies to compile dispositional resources (Humphrey & Aime, 2014; van

Knippenberg, 2017). In general, there are four widely used composition models from cross-level theories and team research: (1) *the additive model* that combines all individual inputs indiscriminately by examining average individual inputs, (2) *the disjunctive model* that relies on the most significant member exclusively by looking at the highest individual input, (3) *the conjunctive model* predicting team outputs with the lowest individual input, and (4) *the dispersion model* that aggregates with variance among individual dispositions (Bell, 2007). Although these four composition models explain most of the team phenomena, each independent team concept does not necessarily fit all four composition strategies simultaneously (Kozlowski & Klein, 2000). For instance, team creativity is intuitively mismatched with the premise of the conjunctive model on the least creative resources or the least creatively capable members.

Nevertheless, despite the significance of both creative dispositions and composition models, existing literature on team creativity rarely takes into account the complexity of team composition models. Most often, creativity scholars adopt the additive model when understanding the relation between creative dispositions and team creativity, as this model represents a simplified approach in both conceptual and mathematical terms (Taggar, 2002). Attempts to explore different composition models were very scarce in the last two decades (Gong et al., 2013; Pirola-Merlo & Mann, 2004), particularly once attention had shifted from team compositions to team processes. Recently, therefore, some creativity scholars have called for more empirical attention to the importance and complexity of team compositions in team creativity research (e.g., Humphrey & Aime, 2014; Mathieu et al., 2014).

Growing Interest in Team Processes in Team Creativity Research

Following the overarching framework of team functioning, configuring creative dispositions and resources should enter collective processes in order to convert into team solutions. Creative process refers to the recurring activities or emergent states that translate creative inputs and structural impacts into team creative outcomes (Taggar, 2002; West, 2002). Team creativity literature has proposed a number of collective processes, from cognitive to motivational and affective processes.

The cognitive approach has so far received the most attention for two main reasons: team research for long has viewed teams as information processors (Hinsz, Tindale, & Vollrath, 1997), and developing creative solutions is an inherently complex cognitive task in which teams generate, recognize, and implement novel ideas (van Knippenberg, 2017). Prior literature tested various team processes such as collaboration (Baer, Leenders, Oldham, & Vadera, 2010), team learning (Kostopoulos & Bozionelos, 2011), information sharing (Madrid, Totterdell, Niven, & Barros, 2015), information exchange (De Dreu, 2006), information elaboration (Hoever, van Knippenberg, van Ginkel, & Barkema, 2012; Rietzschel, Nijstad, & Stroebe, 2007), knowledge integration (Gebert, Boerner, & Kearney, 2010), member influence on decision-making (Gajendran & Joshi, 2012), task reflexivity (Y. Shin, 2014; Somech, 2006), and task conflicts (Miron-Spektor, Erez, & Naveh, 2011). Nevertheless, how information processes unfold individual inputs and synergize into team outputs remains elusive.

Other studies have tested the motivational and affective processes of team creativity. For instance, teams of sequential thinking styles tend to create psychological safety among team members for them to express risky and novel ideas (Post, 2012); inspiring leadership promotes trust among team members to speak up and thus increases team creativity (Boies, Fiset, & Gill, 2015); teams with diverse nationalities tend to develop a higher level of team efficacy to achieve creative successes under diversity training (Homan, Buengeler, Eckhoff, van Ginkel, & Voelpel, 2015); and teams of high functional diversity or gender faultlines generate relational conflicts or emotional conflicts that prohibit team members to share novel ideas (Hüttermann & Boerner, 2011; Pearsall, Ellis, & Evans, 2008). Such motivational and affective processes facilitate the expression and deployment of creative inputs in generating team creative outcomes (De Dreu, Nijstad, Bechtoldt, & Baas, 2011).

It stands to reason that the ultimate deployment of creative inputs is still a cognitive process. Some recent studies have shown that motivational processes affect team creativity by evoking corresponding cognitive processes. For example, Kessel, Kratzer, and Schultz (2012) suggested that psychological safety enhances team creativity via stimulating sharing know-how knowledge within teams. Carmeli, Dutton, and Hardin (2015) similarly reasoned that respectful engagement processes facilitate relational information processes, which then increase team creativity. In other words, motivational processes (or emerged states) act as information inputs in cognitive processes. The essence of creative processes seems to remain cognitive.

Understated Role of Team Structures in Team Creativity Research

That being said, prior explorations on either team composition models or team processes have been oversimplified, not only due to the aforementioned discussions, but also due to insufficient attention to the role of team structures. Earlier studies often understood team structure in terms of task structures in the laboratory settings, such as the nominal structure in which creative activities ought to be carried out in a fixed order (i.e., first individual idea generation and then collective idea synergy) and the interactive structure in which creative activities are mixed and unmonitored (Baruah & Paulus, 2008; Girotra, Terwiesch, & Ulrich, 2010; Kavadias & Sommer, 2009; Paulus & Yang, 2000). Although this indicated how structures may shape the generation of team creativity, it does not capture the spontaneous development and influence of team structure. As put by Kozlowski and Ilgen (2006), “process begets structure, which in turn guides process”. Team structure, defined as regularized relational patterns among team members (Drach-Zahavy & Somech, 2001; Kozlowski & Ilgen, 2006), directs interpersonal interactions in solving team problems.

The structural influence on team creativity may express itself in two forms: On one hand, structured dispositions—the composition models—determine how teams attend to, evaluate, and employ various dispositions (Humphrey, Morgeson, & Mannor, 2009). As discussed above, the notion of structured dispositions was underrated in prior research on creative compositions. On the other hand, structured processes may influence the generation of team creativity via the structural patterns of team activities on both the team level and the subgroup level. Structured processes on the team level have received relatively more attention. For instance, centralized communication structure hinders team creativity as it blocks the diffusion and utilization of novel ideas by prohibiting non-central members from challenging central authority and common knowledge (Leenders, van Engelen, & Kratzer, 2003, 2007; Tang & Ye, 2015). Yet moderately dense communication within teams may be optimal for team creativity (Bhattacharyya & Ohlsson, 2010; Kratzer, Leenders, & Engelen, 2005). Nevertheless, little is known about the more refined picture of team processes on the subgroup level—how subgroups engage in and leverage various team processes. This is in line with van Knippenberg and Mell's (2016) review that not all team processes involve all the team members and, very often, team processes involve only one or a few subsets of individual members. Therefore, a structured view of team processes suggests not only a better understanding of the structural patterns on the team level but, more importantly, a clear picture of who exactly is involved in which processes.

Dissertation Overview

Needless to say, team creativity research requires further examination of not only the independent effects of these three fundamental elements but also the joint effects of them. This is also the aim of the present dissertation—an integrative view of the complexity of composition models, team structures, and collective cognitive processes. Although the overarching theme of this dissertation is team creative performance in organizations, I believe this conceptual framework also can be applied to general team performance, as creativity is one specific form of team performance. Thus, three empirical projects were conducted to advance the literature of both team creativity and team performance by checking integrative views of these three fundamental elements with different data sources and methods.

Three empirical chapters are presented in a chronological order, which reflects how I deepened and broadened my understandings of team creativity and team performance in general, from investigating the boundary conditions of one theoretically significant yet empirically underrated composition model of team creativity to meta-analytically reviewing the major composition models of team creativity, and from concentrating on the interaction patterns among team members to incorporating the impacts of formal team leaders in structured team processes. Despite the conceptual and methodological overlaps between the chapters, these three chapters were developed as stand-alone and can be read independently. In addition, all three projects are the products of collective insights and efforts. Therefore, in the following chapters, I will use “we” instead of “I” to refer to the authors, in order to acknowledge their great contributions to this dissertation.

Chapter 2 examines the boundary condition of a disjunctive model in which the creativity of a team's most creative member predicts team creativity, incorporating a social network perspective, subgroup dynamics, and collective processes. This project answers to the longstanding myth of the importance of creative stars (i.e., the most creative member of a work team) in creativity theories and practices. To understand whether and when team creativity can be improved by the most creative member's inputs alone, we integrate the disjunctive model and insights into team processes. We propose a Disjunctive-Elaboration Model in which team creativity is predicted by the creativity of a team's most creative member only when the subgroup surrounding the "creative star" does not elaborate much information. the main rationale is that high information elaboration enhances synergetic processes that qualitatively alter individual inputs and render a creative star's creativity less predictive of team creativity. Results support this Disjunctive-Elaboration Model of a creative star's influence on team creativity. Moreover, results indicate substituting impacts between creative star's creativity and subgroup information elaboration on team creativity—subgroup information elaboration is positively related to team creativity only when the creative star is less creative. We outline how this testifies to the promise of integrating pooling-of-individual-inputs models like the disjunctive model with models of synergetic processes in team creativity research, and discuss its implication in team research more broadly.

Following the theoretical dispute over different composition models of team creativity, Chapter 3 advances team creativity research by validating the predicting power of two predominant composition models of team creativity (i.e., the additive model vs. the disjunctive model) and identifying boundary conditions at different organizational levels (micro vs. macro) in a meta-analytic review. By coding 114 empirical studies dated between

1980 and 2015, we examined both the prevalent additive model that predicts team creativity from the average individual creativity within the team and the theoretically significant yet empirically underexplored disjunctive model that predicts team creativity from the highest individual creativity in a team. Moreover, following Mathieu, Maynard, Rapp, and Gilson's (2008) framework, we investigated the sensitivity of two aggregation models to the performance environment from two aspects: the micro influence of creativity task demands and the macro influence of industrial sectors. As predicted, average individual creativity (i.e., the additive model) is a stronger predictor of team creativity when team tasks present low creativity demand than high creativity demand, and when in low-tech industries than in high-tech or educational industries. Contrary to our hypothesis, however, the impact of the highest individual creativity (i.e., the disjunctive model) does not differ across performance environments. The findings of Chapter 3 invite team creativity research to pay more attention to the complexity of creativity compositions in work teams, such as within-team differences in member creativity.

Chapter 4 furthermore extends this line of research by examining the influential mechanism of structured compositions. More specifically, this project tests when and how the structural positions (i.e., network center) of team leaders shape the general performance of work teams. Whereas dispositional resources from team members shape the processes and outcomes of work teams to a large extent, leadership intervention is also an indispensable input in team functioning. Prior empirical studies supported a positive role of centralized leadership intervention in team communication networks on team performance (e.g., Balkundi & Harrison, 2006), contradicting the increasing notion of autonomous and empowered teamwork (e.g., Kirkman, Rosen, Tesluk, & Gibson, 2004). We incorporate the social network perspective and contingency theories of leadership, and investigate when and how leader centrality shapes team performance in directed advice networks. Using a multi-source dataset from 72 franchised bakeries of 552 employees and 72 team managers in China, we found that team size moderates the impact of leader centrality in advice-giving and advice-receiving networks respectively. More specifically, leader centrality impedes team performance in the advice-giving network of small teams and in the advice-receiving network of large teams. We found support for a dual-process mediated-moderation model where leader centrality in the advice-giving network of small teams impairs team performance via blocking subordinate collaboration, and impedes team performance through leader's sense of power in the advice-receiving network of large teams.

Chapter 5, finally, outlines the main findings of the presented empirical projects, discusses theoretical implications and contributions to different research streams of team creativity, team compositions and the social network view in team research, and suggests managerial applications for business practices.

Declaration of Contribution

The entire dissertation, from the stage of idea generation to the stage of idea implementation, is a collective product. Hereby I declare the contributions of relevant parties to the different chapters of this dissertation book.

Chapter 1: The majority of work in this chapter was performed by the author of this dissertation independently. Feedback from the promoter and colleagues has been incorporated in revisions.

Chapter 2: Author of this dissertation made substantial contributions to this chapter. The author conceptualized and designed the research model, collected field data in China, analyzed and interpreted data, drafted and revised the manuscript. The promoter provided guidance and feedback in all the aforementioned stages, and provided the final approval to submit to journals. This chapter is currently under Revision & Resubmission at a management journal.

Chapter 3: Author of this dissertation made substantial contributions to this chapter. The author conceptualized and designed the research model, conducted literature review, analyzed and interpreted data, drafted and revised the manuscript. The promoter and another co-author provided guidance and feedback in all the aforementioned stages, and provided the final approval to submit to journals.

Chapter 4: Author of this dissertation made substantial contributions to this chapter. The author conceptualized and designed the research model, conducted literature review, analyzed and interpreted data, drafted and revised the manuscript. The promoter provided guidance and feedback in all the aforementioned stages, and provided the final approval to submit to journals.

Chapter 5: The majority of work in this chapter was performed by the author of this dissertation independently. Feedback from the promoter and colleagues has been incorporated in revisions.

Chapter 2 Creative Star or Teamwork? A Disjunctive-Elaboration Model of Team Creativity

Introduction

In today's knowledge economy, organizations face a myriad of complex and dynamic challenges such as global oversupply and offshoring, fast-changing markets, and high levels of automation and technology. In any business, all these challenges require tailored rather than one-size-fits-all solutions. To achieve and sustain business success in these challenges, organizations increasingly operate in teams and build their competitive advantages on the inimitable capital of creativity (Prabhu, Sutton, & Sauser, 2008; Wuchty, Jones, & Uzzi, 2007b). It has therefore become a vital concern for organizations to acquire and nurture creativity in work teams (Shalley & Zhou, 2008).

One longstanding approach views team creativity as the emergent product of all team members' individual characteristics. Team creativity, then, would result to the extent that individual members either generate creative ideas themselves or encourage them in others, for example through their cognitive styles or creative personalities (L. L. Gilson & Shalley, 2004; Miron-Spektor, Erez, & Naveh, 2007; Miron-Spektor et al., 2011; Somech & Drach-Zahavy, 2013). Of such creativity-related individual characteristics, the one that has been most obviously and directly connected to the question how individual contributions combine to produce team creativity is individual creativity (Bissola, Imperatori, & Colonel, 2014; Taggar, 2002).

An intuitively appealing answer to the question how team creativity results from individual members' creativity is that overall team creativity is primarily contingent on the creativity of the team's most creative member—the "creative star" (i.e., where the label of "star" merely is shorthand for the most creative member in the team and does not necessarily imply high creativity in an absolute sense). Examples can be found in various industries, from engineering science (e.g., Nikola Tesla and his engineering teams) to the entertainment industry (e.g., Woody Allen and his collaborators). Such examples illustrate that creativity is more about the rare and extreme than about the average and common (Girotra et al., 2010; Ready, Conger, & Hill, 2010). Accordingly, it seems plausible that team performance on creative tasks is disjunctive, that is, primarily determined by creativity of its most creative member (Steiner, 1972). Nevertheless, empirical evidence for this disjunctive model of team creativity is scarce—more prevalent is the additive model conceptualizing team creativity as determined by the sum or average of individual members' creativity (G. Chen, Mathieu, & Bliese, 2003; Klein & Kozlowski, 2000; Taggar, 2001). Out of all empirical studies on team creativity, only two hypothesized the disjunctive model (Taggar, 2001; Triandis, Bass, Ewen, & Mikesell, 1963), together with another two reporting relevant statistics as supplements (Gong et al., 2013; Pirola-Merlo & Mann, 2004). Yet, these four empirical tests did not conclude on its validity, with two studies supporting the positive influence of creative star's creativity on team creativity (Gong et al., 2013; Triandis et al., 1963), and two studies reporting positive but insignificant correlations (Pirola-Merlo & Mann, 2004; Taggar, 2001).

Though favoring its logic, we believe that the disjunctive model of team creativity in and of itself is oversimplified. Team-level processes, as suggested in Taggar's (2002) team creativity model, play a vital role in combining and integrating individual inputs and should not be overlooked. Hence, the disjunctive logic may be more fruitfully applied to team creativity by taking into account how insights from creative stars get attended, processed and altered in collective processes (cf. De Dreu, Nijstad, & van Knippenberg, 2008; Hinsz, Tindale, & Vollrath, 1997). Defined as the exchange, discussion and integration of different views to create new solutions (van Knippenberg, De Dreu, & Homan, 2004), information elaboration outlines the prototypical process of information synergy in teams (Hoever, van Knippenberg, van Ginkel, & Barkema, 2012). It increases both coverage and synthesis of individual inputs in team solutions—the more teams engage in information elaboration, the more altered and less weighted individual ideas are (van Ginkel & van Knippenberg, 2008). As a consequence, we may infer that when elaboration is low instead of high, team creativity is not so much a collaborative creative effort, but rather the product of only the star member's creative effort, as the disjunctive model proposes. More specifically, we propose that what matters here is information elaboration in the immediate subgroups surrounding creative stars. This is not only because teams hardly process information as unitary entities (Carton & Cummings, 2012, 2013; Putnam, 1988), but especially because ubiquitous subgrouping causes divided information sharing and processing patterns in teams (Carton & Cummings, 2013; Gibson & Vermeulen, 2002; Halevy, 2008). Therefore, selecting and processing creative star's ideas is more a matter of intra-subgroup processes than of overall team processes. We thus propose a Disjunctive-Elaboration Model in which creative star's creativity predicts team creativity only when information elaboration in the creative star's subgroup is low.

Thus, we propose that a disjunctive model that looks only at member characteristics in predicting team creativity is simplistic, while ignoring collective processes and subgroup structures is doomed to yield inconsistent results. The current Disjunctive-Elaboration Model takes into account the role of subgroup information processes and thus represents an important step forward in reconciling the understanding of the disjunctive logic of team creativity with insights in the complexities of team processes. This is also important because current team creativity research, let alone team research in general, seems to be dominated by the implicit assumption that team members all engage in a unitary process of information exchange and integration, and contribute equally to team performance (Taggar, 2002). The contribution of our study thus lies not only in developing and testing a Disjunctive-Elaboration Model of team creativity that integrates insights in collective information processes and subgroup structures, but also in providing a counterpoint to the mainstream of team creativity research that understates the importance of key players (cf. Zhou & Hoever, 2014)—in this case creative stars and their subgroups. A more indirect implication of our research is that it may also encourage other streams of team research to study key team players in team processes rather than treating all team members as homogeneous and interchangeable.

Theory and Hypotheses

From Individual Creativity to Team Creativity: A Disjunctive Model

Creativity in the workplace is defined as the generation of both novelty and usefulness in products, services, processes, and other outputs (Amabile, 1988b, 1996; Oldham & Cummings, 1996). This definition has a multilevel focus stating that creativity occurs across organizational levels (Drazin, Glynn, & Kazanjian, 1999; Woodman et al., 1993). Individual creativity is subject to contextual supports and constraints such as job descriptions, reward systems, and coworkers' performance (Shalley & Gilson, 2004). But more importantly, it is rooted in individual differences such as abilities, expertise, and personality (Gough, 1979; Kirton, 1976; Mumford & Gustafson, 1988). For example, some individuals consistently display higher creativity than others (Gough, 1979; Staw, 2009). This longstanding notion acknowledges the variation among individuals in their propensity to be creative (van Knippenberg & Hirst, 2015), and raises an obvious question for team creativity research that whether and how team creativity—the production of creative solutions concerning products, services, and procedures in collective processes (Shalley, Zhou, & Oldham, 2004)—can be understood through individual creativity of team members.

It is not new in creativity research to view team creativity as linked to the characteristics of particular members. For instance, Taggar (2001) and Miron-Spektor, Erez, and Naveh (2011) demonstrated that the proportion of highly creative team members (i.e., those who score in the top 20 percent on creative thinking styles) promotes team creativity and innovation. In understanding how creativity of individual members may contribute to team creativity, an important consideration is that teams would presumably determine which ideas to pursue for further development, and prioritize ideas that appear most novel and useful (George, 2007; Girotra et al., 2010; Shalley & Gilson, 2004). Individual creativity thus would not add up to team creativity indiscriminately—or at least, such an additive model would not capture team's recognition of better and worse creative contributions. In contrast to the additive model, a disjunctive model captures this notion of teams discriminating between more and less creative contributions from individual members, and prioritizing individual contributions that are most creative. Derived from the notion of disjunctive task in Steiner's (1972) typology, a disjunctive model of team creativity would suggest that the creativity of teams' most creative members—creative stars—is primarily predictive of team creativity. Such an emphasis on creative stars is also aligned with the increasing attention to star performers as most predictive of team performance (Aguinis, O'Boyle, Gonzalezl-Mulé, & Joo, 2015; O'Boyle & Aguinis, 2012).

Despite the intuitive appeal of the disjunctive model, very few empirical studies have actually looked into it (Gong et al., 2013; Pirola-Merlo & Mann, 2004; Taggar, 2001; Triandis et al., 1963). Most studies exclusively view the emergence of team creativity as additive, paying little attention to alternative approaches. The reason might be twofold. First, creativity researchers are deeply influenced by the additive model in multilevel research, which sums individual contributions regardless of their variance. Although Chan (1998) proposed five different models for bottom-up impacts, the additive model pervades in nearly all multilevel research for both conceptual and computing reasons (G. Chen et al., 2003; Klein & Kozlowski, 2000; Taggar, 2001). As a consequence, although researchers aimed to reveal the emerging process of team creativity from individual creativity, the disjunctive model was not taken into account (e.g., Taggar, 2002). Second, inconsistent results for the disjunctive model may discourage scholars from further investigation. As mentioned before, reported findings on the relationship between highest individual creativity and team creativity are not consistent. Advocatory evidences were presented in two studies (Gong et al., 2013; Triandis et al., 1963). But the other two found no support for this disjunctive model (Pirola-Merlo & Mann, 2004; Taggar, 2001).

We believe that these inconclusive results are due to the oversimplification of the disjunctive model in its pure form. As Hackman (2003) suggested, it is inappropriate to explain any team construct with only the properties of constituent parts. From the perspective of multilevel analysis, collective constructs emerge from synthesis of lower-level elements (Cronin, Weingart, & Todorova, 2011; Ilgen et al., 2005; Morgeson & Hofmann, 1999). Creativity researchers also have underlined the importance of collective processes that transform individual creativity into team creativity (Hargadon & Bechky, 2006; Taggar, 2002). The generation of team creativity is not only about the presence of good ideas, but also about their integration and development (Bechtoldt, De Dreu, Nijstad, & Choi, 2010). Here lies a shortcoming of the disjunctive model in its pure form: it is a pooling-of-individual-inputs model in which teams pool individual contributions and select the most creative contribution(s)—presumably those from creative stars. Even when team creativity is essentially driven by particular individual contributions, team process may or may not focus on the further development and refinement of such contributions.

The issue is not that team creativity would be better explained by the additive model, which is also a pooling-of-individual-inputs model with limited room for the influence of team processes. Rather, we propose that the issue is that a more accurate model of how individual creativity contributes to team creativity would do more justice to synergetic team processes that substantially alter individual contributions and reduce the predictive power of individual creativity for team creativity. This notion of the synergetic integration and development of creative contributions is closely aligned with the notion of teams as information processing systems (De Dreu et al., 2008; Hinsz et al., 1997). As we outline in the next section, this approach would suggest that the synergetic processing of information (i.e., information elaboration) is a key contingency of the predictive validity of the disjunctive model, in that lower elaboration would be associated with a stronger influence of individual contributions, whereas higher elaboration would be associated with synergetic processes that render individual contributions less predictive of team creativity.

Information Elaboration in Creative Star's Subgroup: A Disjunctive-Elaboration Model

The concept of information elaboration—the exchange, discussion, and integration of task-relevant information and perspectives—was proposed to capture the notion of synergetic information processing in teams (Homan, van Knippenberg, van Kleef, & De Dreu, 2007; van Knippenberg et al., 2004). Whereas this concept was broadly advanced to capture synergetic processes in all team tasks with information integration requirements (e.g., team problem-solving, team decision making; Homan et al., 2008, 2007; van Ginkel

& van Knippenberg, 2008), it is highly relevant for team creativity where creativity may arise from synergetic integration of different member contributions (Hoever et al., 2012). Teams engaging in high levels of information elaboration incorporate different members' information, ideas, and perspectives into holistic team products, whereas teams with low information elaboration select from member contributions rather than synthesize them—team products reflect less integration and development of individual contributions.

From the perspective of information elaboration as capturing synergetic team process, we propose that information elaboration moderates the relationship between star member creativity and team creativity. More specifically, the disjunctive model in which star member's creativity predicts team creativity only holds with low information elaboration of their inputs. The rationale is that low information elaboration provides a setting in which teams pool individual contributions, and teams are likely to select the most creative individual ideas—most likely those of team's creative star. This tendency should be strengthened by the fact that, as Morrison & Vancouver (2000) suggested, individuals with greater expertise are more likely to be sought out for advice and feedback. Selection of creative star's ideas may thus not only revolve around the greater creativity of his/her contributions in a given case, but also arises from greater attention to creative star's contributions in matters requiring creativity. In contrast, high levels of information elaboration should reduce the predictive power of creative star's individual creativity. Information elaboration entails the integration and further development of various individual contributions, suggesting that individual inputs become less identifiable in, and less predictive of, the final team product. When it comes to the predictive power of the disjunctive model, then, we may propose that this is stronger under low information elaboration than under high information elaboration.

We propose that information elaboration moderates the relationship between star member creativity and team creativity, but we do not see this as revolving around information elaboration in the entire team as if the team is a homogeneous entity in which all members equally participate in all team processes. Rather, we see the role of information elaboration as concerning elaboration within the subgroup in which the creative star is embedded. From the perspective of maximum engagement of all members it may be ideal when all team members equally engage in the information elaboration process. In reality, however, the existence of subgroups is deeply entrenched in team activities (Carton & Cummings, 2012), and information elaboration is more likely to revolve around subgroup processes (Putnam, 1988). Teams tend to develop distinctive subgrouping patterns due to differences in demographic factors, economic and social status, and information (Carton & Cummings, 2013). Unevenly distributed information connections thus result in fragmented team functioning in smaller subgroups (Gibson & Vermeulen, 2002; Lau & Murnighan, 1998, 2005; Levine & Moreland, 1998), where high levels of communication within subgroups does not always imply information exchange and coordination across subgroups (Carton & Cummings, 2013; Halevy, 2008). Thus, from the perspective of information elaboration as a synergetic process that may reduce the predictive power of creative star's creativity, the more precise focus would be on information elaboration within the subgroup in which the creative star is embedded (for short: subgroup information elaboration). Thus, we predict:

Hypothesis 1: Star member creativity is more positively related to team creativity with low subgroup information elaboration than with high subgroup information elaboration.

Hypothesis 1 addresses the contingent predictive power of the disjunctive model.

It does not address the question whether team creativity would be higher with higher information elaboration or with lower information elaboration. Even when the synergetic processes captured by information elaboration may drive team creativity (Hoever et al., 2012), it is not necessarily the case that relying on this synergetic process leads to higher creativity than relying on the contributions of creative stars. Indeed, as we outline in the following, we propose that even though information elaboration should be positively related to team creativity, this influence is weaker as the creativity of team's creative star gets higher—with higher star member creativity, information elaboration will be less able to add above and beyond the star's input. Note that this hypothesis statistically concerns the same interplay between star member creativity and subgroup information elaboration on team creativity. But while hypothesis 1 focuses on the impact of star member creativity, hypothesis 2 outlined in the following focuses on the influence of subgroup information elaboration.

The rationale for our prediction here has its basis in the disjunctive logic. The disjunctive model applied to team composition reflects an ability model: in tasks where team performance is determined by the best individual performance, best performers are recognized by their greatest performance-relevant skills and abilities. In the context of team creativity, this determining factor translates to the creativity of the team's creative star—the member of best capability to generate outcomes with high levels of creativity. Because individual creativity to a substantive degree is a matter of skills and ability (Amabile, 1988b; Staw, 2009). Hence, as the star gets more creative, it is increasingly challenging for the collaborative effort of team information elaboration to add value to the input of the team's creative star. Put differently, as the team's creative star is more creative, other members will find it more difficult to introduce creative improvements to the star's input. The implication is that with higher star member creativity, subgroup information elaboration has less added value for team creativity.

> *Hypothesis 2: Subgroup information elaboration is more positively related to team creativity with low star member creativity than with high star member creativity.*

Methods

Data and Sample

Sales teams of seventy-five bakery stores from one company in the central part of China participated in this study. This company is known for its novel products and services in the baking industry of China. Sales teams are empowered to initiate novel customer services and sales strategies, such as special catering for students' second lunch during recesses, and launching doorstep delivery service to student dorms. Creative performance is rewarded with a year-end bonus by stores. Teamwork is required for sales strategies such as providing consultancy on large purchases. Due to the nature of franchised stores, all teams work in relatively comparable circumstances but operate independently. Employees are encouraged to exchange expertise and sales techniques, which enables intense communication and cooperation within teams. All these enable us to observe team creativity and information elaboration in this setting.

We sent paper-and-pencil surveys to all sales members and team leaders (i.e., shop managers) in two weeks. In the first week, subordinate surveys were administered on site. In the second week, all leaders were administrated to fill in the supervisor survey during their monthly review meeting in headquarters. Meanwhile, we obtained corporate assessments of team creativity from the HR office in headquarters. Later reminders were sent to all absent employees and leaders.

567 out of 577 employees filled out the subordinate questionnaires and 73 out of 75 teams filled out the supervisor counterparts. After matching supervisors' ratings on individual creativity with corporate assessments on team creativity, we discarded seven teams due to the lack of corporate assessments, leaving 66 out of 75 teams—a valid response rate of 88 percent. Because a high response rate in each team is necessary for accurate analyses on team level, we removed four teams with a response rate below 80 percent, following the suggestions in previous team studies (Oh, Chung, & Labianca, 2004; Sparrowe, Liden, Wayne, & Kraimer, 2001). Two teams with only three members were discarded, because the minimum size of a subgroup is three in our subgroup analysis with social network tools (Borgatti, Everett, & Johnson, 2013). The final sample consisted of 483 employees from 60 teams of 4 to 21 members[1] (M_{size} = 8.05, SD_{size} = 3.31).

Measures

Team creativity. We obtained KPI (Key Performance Index) scores on team creativity from the HR executive in headquarters, on a 100-point index. The scores covered two parts: a) service increments by generating and/or meeting customers' new needs, and b) strategy contributions by suggesting and applying novel and helpful ideas on product development and/or sales strategies. Teams receive corresponding year-end bonus and recognition according to their creativity scores.

Star member creativity. Team leaders assessed each subordinate's creative performance using Farmer, Tierney, & Kung-Mcintyre's (2003) 4-item scale on a 10-point basis (1 = "Strongly disagree", 10 = "Strongly agree"; α = .85). This scale has been translated

[1] An outlier team was detected on team size n = 21, $z > 3.29$, $p < .001$. We kept this team in our sample for team size was not of main concern in this study. Excluding this team did not change our results.

and validated in previous creativity studies in China (H. Zhou & Long, 2011). Sample items are, “this employee seeks new ideas and ways to solve problems”, and “this employee is a good role model for creativity”. Creative star in each team is identified as the member(s) that score highest on this measure. Most of teams have one creative star. One team has two stars of highest scores, and two teams have same scores on all members[2].

Subgroup of creative star. To determine the subgroup in which the creative star is embedded, we employed subgrouping techniques from social network analysis. Social network research has a history of identifying subgroup structures in local networks based on the interpersonal ties between members (Borgatti et al., 2013; Burt, 2004). In this study, we focused on the information flow of work-related advice, which is of the most relevance to collective information processing (Sparrowe et al., 2001). We adapted Borgatti, Everett, and Johnson's (2013) subgroup analysis to assess subgroup structures in teams, instead of using Borgatti & Everett's (2000) core-periphery structure measure. This is because core-periphery structure stringently assumes only one subgroup as core and loosely connected peripheral members as periphery, and thus does not apply to work teams with multiple subgroups. Team researchers have found that large teams (i.e., with team size above 9) are very likely to have complex structures of multiple subgroups (Carton & Cummings, 2012; Meyer & Glenz, 2013). In our sample, team size varies from 4 to 21 (M_{size} = 8.05)[3]. Hence, a structural analysis that incorporates possibility of multiple subgroups serves this study best.

Directed advice network data was collected via rosters, which has been widely deployed for improving recalls in network research (Perry-Smith, 2006; J. Zhou, Shin, Brass,

[2] We kept these teams in our analysis. Team of two stars does not raise an issue on our analysis, as two stars locate in the same subgroup. On the other hand, excluding either two teams of same creativity scores on all members or all these three teams did not change our results.

[3] Out of 60 teams, 15 teams have at least two subgroups.

Choi, & Zhang, 2009). Notably, we specify the advice network question as advice-giving instead of general advice communication or advice-seeking. This is because, advice-giving ties captures the actual information flows in resolving task-related issues, while advice-seeking is often obscured by social contacts for the purpose of impression management (Liljenquist, 2010) . Employees were requested to report “To what degree do you give this person professional advice when he/she has work-related problems?” on each team member listed on rosters, on a 6-point Likert scale (1=” less often”, 2 = “several times a year”, 3 = “once a month”, 4 = “several times a month”, 5 = “several times a week”, 6 = “daily”).

Analysis of subgroup structure is summarized as followed: 60 team networks were first dichotomized at a cutoff of “4” in UCINET (Vital & Martins, 2009), as subgrouping analysis tools are restrained to only binary networks (Borgatti et al., 2013). Dichotomization also fits our sampling site of franchised stores. Because team members tend to have intensive communications and are less likely to interact “several times a year”. For comparison we also fractioned all valued networks with optimization algorithm in accordance to Borgatti, Everett, and Johnson's (2013, p. 199) suggestions. This allows us to examine (a) whether dichotomization changes subgrouping structures, and (b) whether there are any subgroups in teams of less frequent communications. We then conducted clique analysis with overlapping pattern on dichotomized matrixes to detect possible subgroups. A clique is a maximal subgroup of at least three members in which any two members are connected. Overlapping clique analysis allows individuals to join more than one clique, at the expense of clear-cut subgroup structures (Borgatti et al., 2013). Given individuals tend to hold only one primary subgroup identity despite multiple membership (Carton & Cummings, 2012), we disentangled overlapped cliques into distinctive subgroups by conducting hierarchical clustering analysis on co-membership matrices. This technique recognizes consistent subsets across overlapping cliques as stable subgroups[4]. Eight teams were found of no subgroup. In order to examine whether there indeed exists no subgroup or dichotomization obscures loose subgroup structures (individuals connect with less frequent advice-giving ties under "4"), we used fractioned valued networks to double check if any loose subgroups can be detected. This yielded six teams of loose subgroups and two teams of no subgroup at all.

Subgroup information elaboration. Information elaboration was assessed on individual level with three items from Homan and colleagues (2008), on a 10-point scale (1 = "Strongly disagree", 10 = "Strongly agree"; $\alpha = .81$). A sample item is, "During the task, we tried to use all available information". We aggregated information elaboration on creative stars' subgroups. The inter-rater agreement and consistency indices were tested to validate our aggregation on mean ratings. ICC (1) was .55 (F [353, 708] = 4.65, $p < .001$, BCa 95% CI = [0.49, 0.60]), and ICC (2) was .79 (F [353, 708] = 4.65, $p < .001$, BCa 95% CI = [0.74, 0.82]). The R_{WG} statistic yielded a score of .79. According to LeBreton & Senter (2007), an ICC (1) scoring above .40 implies substantial effect size for grouping, and an ICC (2) scoring above .70 and R_{WG} scoring above .80 suggest agreement among group members. Thus, our aggregation on mean ratings was justified.

Control variables. In this study, we controlled team size, average creativity of non-star members, and team extraversion. Prior studies have showed team size as an important predictor of team structure and team creativity (Menon & Phillips, 2011; West & Anderson, 1996). Larger teams often have complex structure which influences team processes directly

[4] A set of four indices provided in UCINET was referred to facilitate adequate interpretation of the hierarchical clustering analysis, namely Eta, modularity Q, and Q-prime all scored positive and E-I index. We identified the clustering when Eta, modularity Q, and Q-prime all scored positive and E-I index scored negative.

and indirectly (Meyer & Glenz, 2013). To examine the unique contribution of creative stars, we also need to control the confounding effect of average creativity among team members on team creativity, as prior studies evidenced a positive correlation between average creativity of team members and team creative outputs (Gong et al., 2013; Taggar, 2002). In this model, the average creative performance of non-star members was controlled in order to exclude the share of creative star in average creativity. Lastly, team extraversion is also controlled, as extravert individuals are prone to engage in social activities and to exchange information, and thus impact on team creativity-relevant processes (Taggar, 2002).

Analysis and Results

Table 1 reports means, standard deviations, and correlations of variables in regression models. Table 2 shows the regression results of for our hypothesis test.

Table 1. Means, Standard Deviations, and Correlations [a]

	Variables	Mean	s.d.	1	2	3	4	5
1.	Team creativity	59.29	10.59					
2.	Star member creativity	7.22	1.50	.16				
3.	Subgroup information elaboration	7.48	0.79	.13*	.01			
4.	Team size	8.05	3.31	.35**	.27*	.15		
5.	Average creativity of non-star members	5.52	1.35	-.12	.59**	.03	.04	
6.	Team extraversion (mean)	6.12	1.35	.29*	.04	-.02	.20*	-.01

[a] $N = 60$.

* $p < .05$, ** $p < .01$.

As expected, subgroup information elaboration negatively moderates the relationship between star member creativity and team creativity ($\beta = -.25$, $t = -2.02$, $p < .05$, BCa 95% CI = [-5.98, -0.02], ΔR^2 = .05). To further interpret the relationship of star member creativity and subgroup information elaboration with team creativity, we conducted simple slopes analyses (Aiken & West, 1991). Results suggest that star member creativity is positively related to team creativity when subgroup information elaboration is low (b = 6.36, t = 2.63, p = .0), and is not related to team creativity when subgroup information elaboration is high (b = 0.36, t = 0.18, p > .1). Figure 1 displays this interaction pattern.

Table 2. Regression results on Hypothesis [a]

Variables	β	t	95% confidence interval	
			Lower	Upper
Hypothesis 1				
Team size	0.17	1.32	-0.94	4.55
Average creativity of non-star members	-0.33	-2.26*	-6.69	-0.39
Team extraversion (mean)	0.26	2.22*	0.27	5.33
Star member creativity	0.32	2.05*	0.07	6.64
Subgroup information elaboration	0.07	0.60	-1.76	3.28
Star member creativity × subgroup information elaboration	-0.25	-2.02*	-5.98	-0.02
R^2	.29*			

a. Dependent variable: team creativity. N = 60.

* p < .05.

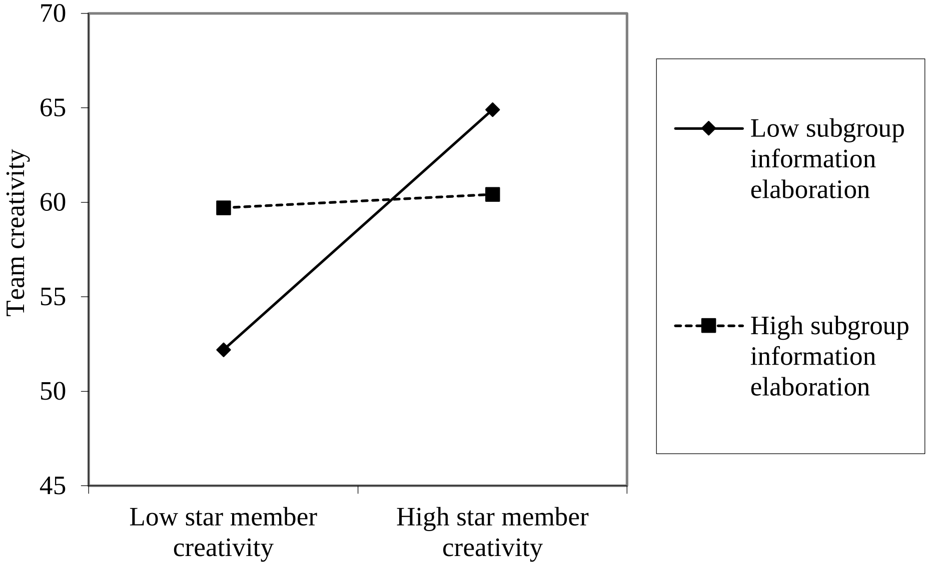

*Figure 1***.** Subgroup information elaboration as a moderator of the relationship between star member creativity and team creativity

We also analyzed the simple slopes of subgroup information elaboration in the same interaction effect to test hypothesis 2. Subgroup information elaboration was found positively related to team creativity when star member creativity was low (b = 3.76, t = 2.08, p < .05), but unrelated to team creativity when star member creativity was high (b = 2.24, t = -1.08, p > .1). For ease of interpretation, Figure 2 recasts Figure 1 in terms of elaboration slopes. Thus, both hypothesis 1 and 2 are supported.

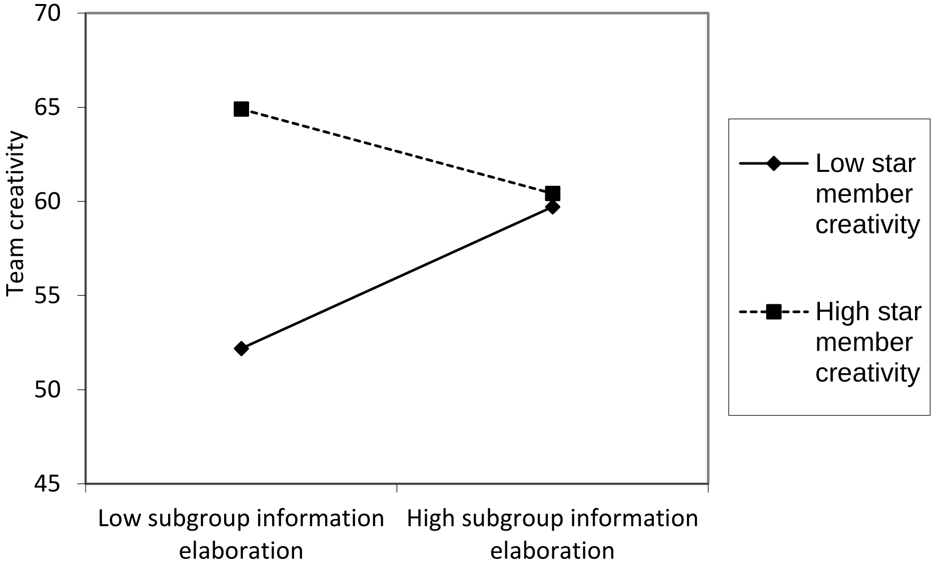

Figure 2. Star member creativity as a moderator of the relationship between subgroup information elaboration and team creativity

Complementary Analyses

In this study, we developed and supported a Disjunctive-Elaboration Model of team creativity in which creative star's creativity predicts team creativity when subgroup information elaboration is low. To consolidate our argument about the subgroup as the actual unit of information elaboration, we tested an alternative disjunctive model with overall team information elaboration as a moderator (alternative Hypothesis 1). As shown in Table 3, while creativity of star members still holds a marginally positive impact on team creativity (β = .27, t = 1.73, p < .1, 95% CI = [-0.45, 6.07]), the interaction term between star member creativity and team information elaboration yields no influence (β = -.16, t = -1.31, p > .1, 95% CI = [-7.29, 1.53]). This reinforces our finding that what matters to the validity of disjunctive model is the information elaboration of creative star's subgroup rather than the overall team.

Another question is whether our analysis would also hold for the additive model. The additive model too is a pooling-of-individual-contributions model, and thus might also hold more under conditions of low information elaboration (or might hold regardless of information elaboration). Our conceptual analysis led us to favor the disjunctive model over the additive model, but testing the alternative model would provide additional insights in the formation of team creativity via different approaches. We therefore conducted an additional analysis to test the predictive power of average member creativity, controlling for team size and team extraversion (alternative Hypothesis 2). The simple additive model was not supported (β = -0.11, t = -0.91, p > .1, 95% CI = [-3.30, 0.97]). We also tested the moderating role of team information elaboration in the additive model (note that subgroup information elaboration is not relevant here, because the additive model adds all members' creativity, alternative Hypothesis 3). No significant interaction was found (β = -0.09, t = -0.75, p >.1, 95% CI = [-1.19, 3.12], see Table 3 for a comprehensive view).

Table 3. Regression results on complementary analyses [a]

Variables	*β*	*t*	95% confidence interval	
			Lower	Upper
Alternative Hypothesis 1 (disjunctive-team elaboration model)				
Team size	0.23	1.83†	-0.23	5.12
Team extraversion (mean)	0.24	2.03*	0.02	5.11
Average creativity of non-star members	-0.29	-1.99†	-6.26	0.03
Star member creativity	0.27	1.73†	-0.45	6.07
Team information elaboration	0.13	1.11	-1.14	3.93
Star member creativity × team information elaboration	-0.16	-1.31	-4.67	0.98
R^2	.27			
Alternative Hypothesis 2 (the additive model)				
Team size	0.31	2.49*	1.06	5.42
Team extraversion (mean)	0.23	1.85†	0.23	4.60
Average member creativity	-0.11	-0.91	-3.30	0.97
R^2	.19			
Alternative Hypothesis 3 (the additive-elaboration model)				
Team size	0.30	2.42*	0.98	5.34
Team extraversion (mean)	0.23	1.88†	0.27	4.65
Average member creativity	-0.10	-0.80	-3.20	1.23
Team information elaboration	0.17	1.38	-0.38	3.94
Average member creativity × team information elaboration	0.09	0.75	-1.19	3.12
R^2	.22			

a. Dependent variable: team creativity. $N = 60$. † $p < .1$, * $p < .05$.

Discussion

Incorporating insights from research on team information processing and on subgroup structures, this study extends and develops the disjunctive model of team creativity into a Disjunctive-Elaboration Model. We examined the moderating role of subgroup information elaboration in the relationship between star member's creativity and team creativity. Results supported our hypothesis 1 that creative star's creativity is positively related to team creativity when information elaboration is low in the subgroup in which the star is embedded. Moreover, addressing the question when relying on the mechanisms captured by the disjunctive model (i.e., selection of individual members' best contributions) or relying on information elaboration is more valuable for team creativity, results confirmed hypothesis 2 that information elaboration is positively related to team creativity only when star member creativity is low. These findings have implications for team creativity research as well as for team research more broadly.

Theoretical and Practical Implications

The disjunctive model of team creativity recognizing the contribution of a star performer to creative performance in team contexts is consistent with the strong emphasis on individual differences in creativity research (see van Knippenberg & Hirst, 2015; Zhou & Hoever, 2014, for reviews). As a pooling-of-individual-contributions model, however, the disjunctive model does little justice to the influence of collaborative processes in in generating creative outcomes in teams. Combining these two views, it is probably not surprising that the disjunctive model in which the creativity of the team's most creative member—its creative star—predicts team creativity is supported in prior research, yet not consistently supported. The variance in findings for the disjunctive model led us to extend and develop the disjunctive model into a Disjunctive-Elaboration Model that incorporates the moderating role of synergetic subgroup information elaboration processes and thus recognizes the validity of both the creative star perspective and of the synergetic information process perspective.

A direct implication of this Disjunctive-Elaboration Model is that it should not just hold for a direct assessment of individual creativity, but also for individual differences that are precursors to individual creativity and documented in the creativity literature, such as cognitive ability (Batey & Furnham, 2006), creative personality (Gough, 1979), cognitive style (Kirton, 1994), and openness to experience (see Feist, 1998, for a meta-analysis, and van Knippenberg and Hirst, 2015, for a recent review). Following that same logic, factors that have been identified as precursors to team information elaboration can also be expected to have a similar moderating role (see van Knippenberg et al., 2004, for a more elaborate discussion in this respect), and include team composition in terms of individual differences such as need for cognition (Kearney, Gebert, & Voelpel, 2009) and situational influences such as time pressure (Kruglanski & Webster, 1991). Obviously, we would not conclude from the current findings that these proposition also hold—this is for future research to determine—but these implications are important because they suggest that the disjunctive-elaboration model does not only apply to two specifically defined variables as studied in the current study, but applies to two *classes* of variables—individual differences associated with individual creativity, and dispositional and situational influences associated with information elaboration.

The logic underlying the Disjunctive-Elaboration Model may also apply to team performance beyond team creativity. van Knippenberg, De Dreu, and Homan (2004) outlined how information elaboration has synergetic benefits for tasks with information integration requirements—knowledge work. Such benefits would for instance express themselves not only in creativity (and innovation), but also in the quality of decision making and problem-solving. Following their analysis, we may propose that these are all tasks where the quality of team's star member could drive team performance with lower information elaboration, whereas information elaboration would render the star's performance less predictive of team performance because the synergies captured by information elaboration would add to and change individual contributions. The validity of this proposition is for future research to determine, but this proposition is indicative of our Disjunctive-Elaboration Model's potential to apply more widely to knowledge work and to not be limited to team creativity.

Our study was designed to address the conditions under which the disjunctive model of team creativity would hold, and not to pit the disjunctive model against the additive model. Results provide evidence for our moderation perspective on the disjunctive model and do not yield support for the additive model, but the latter should be interpreted in the light of other studies advocating the additive model (e.g., Bissola et al., 2014; Pirola-merlo & Mann, 2004). We would therefore refrain from strong conclusions regarding the merits of the additive model, and would leave more explicit comparisons of the two models to future research. In this respect, we may note that team tasks may be a boundary condition for the predictive validity of the disjunctive model—some tasks may favor the additive model over the disjunctive model (Steiner, 1972). The implicit assumption underlying the disjunctive model is that contributions of different members are interchangeable—functional roles of individual members are relatively homogeneous such that whoever is most creative could be the primary contributor to team creativity. This would for instance be the case in our bakery sample, where all team members should in principle be qualified to come up with creative ideas within the same domain. When functional roles are heterogeneous among individual members, however, such as the case in cross-functional teams, team performance—and thus also team creativity—may rely more on the quality of creative contributions from each particular function. That is, in such situations, the team may rely more on members (or at least on each functional area) to make a unique contribution from their unique expertise. One particular member's creativity, therefore, may compensate less for the lower creativity of the other, because the team relies on creative contributions from all different functional areas. In such teams where heterogeneous functions invite task interdependence among members (cf. Gully, Devine, & Whitney, 1995), the additive model may be more important than the disjunctive model.

Theoretical considerations led us to favor a focus on subgroup information elaboration, and this analysis was corroborated at least in the sense that our model was supported whereas alternative team-as-a-whole models were not. Given that we did not directly test the validity of a subgroup approach versus a unitary team approach, we remain tentative in our conclusions here. With that caveat in mind, we suggest that future team research may benefit from abandoning the implicit assumption that team processes are homogeneously experienced and shared by all members, and exploring the impact of subgrouping in this respect. Whereas we are not the first to suggest so conceptually (Putnam, 1988) or to study this empirically (e.g., Carton & Cummings, 2013; Gibson & Vermeulen, 2002; Halevy, 2008), studies following a subgroup approach to disentangle team processes are far from sufficient. Our evidence for the subgroup approach calls for team researchers to fully develop the subgroup perspective empirically.

Implications for Practice

Creativity research has a long tradition of emphasizing the role of creative stars—to view creativity as an outcome with strong roots in individual differences. One way to look at our results then is to note that they show that synergetic efforts as captured by information elaboration can substitute for high star member creativity. In that sense, organizations could focus on attracting and retaining creative stars or on fostering collaborative information process, but an investment in both may have diminishing returns on investment.

Our findings suggest that developing teams for information elaboration (van

Knippenberg, van Ginkel, & Homan, 2013) may be a way to stimulate team creativity in the absence of real creative stars. At the same time, results also show that with high star member creativity, information elaboration does not add to team creativity. Indeed, even when the slope is not significant, the pattern of results is actually such to suggest that with real creative stars, information elaboration might actually temper the level of creativity—perhaps because greater collaborative efforts to be creative may also inspire a desire to incorporate all individual contributions in the team product (cf. Runco, 2003), which may result in less creative products than when the team would prioritize the contributions of a real creative star. It thus may be wise to let the emphasis on information elaboration versus a focus on star member contributions be in part determined by the extent to which the team's creative star is a star in an absolute sense or only in a relatively sense within the team. Although this observation comes with the caveat that it only represents a trend in our data and future research is needed, there is at least an indication that with real creative stars in teams, a focus on synergetic team processes may be suboptimal. Put more in terms of HR practices, it might be wise to decide to either focus on attracting and cultivating creative stars or on developing synergetic team processes but not on both.

Limitations and Future Directions

Despite its strength, this study has some limitations that we hope to address in future work. First, although there is no conceptual evidence suggesting a reversed causal link, a longitudinal design will provide stronger evidence for our hypotheses than the current cross-sectional design. Experimental research to might be valuable to complement field evidence with causal evidence.

We examined our model in bakery industry rather than R&D industries such as pharmaceutical and computer industries. It is possible that in industries where creativity is more a core business, team members are more skilled in developing ideas through synergetic information processes and there is less a case of diminishing returns on elaboration with higher star member creativity. Put differently, the type of industry (i.e., industries where creativity is valuable but not core to business vs. industries where creativity is core to business) may constitute a boundary condition to the current pattern of results.

Besides, individual creativity in this study was reported by team leaders rather than objective scores. This is more or less inevitable given the nature of the work and the absence of more objective measures, but ideally future research would yield complementary evidence that is less subjective.

Another possibility for future research to explore would be whether this Disjunctive-Elaboration Model would explain radical and incremental creativity differently. Research suggests that quality of single creative input matters more in radical than in incremental creativity (Madjar, Greenberg, & Chen, 2011). It may thus also be the case that the disjunctive model is more predictive of radical creativity than of incremental creativity, and that information elaboration has a stronger attenuating effect on the predictive power of the disjunctive model on radical creativity.

Conclusion

The behavioral study of creativity at work in a sense is characterized by two separate traditions: one focuses on individual differences, and the other emphasizes the creative value of synergetic team work. The present study shows that these two approaches can be fruitfully integrated for a better understanding when the creativity is more likely to be driven by creative stars and when more by synergetic elaboration processes. This integration in our Disjunctive-Elaboration Model has clear implications for two classes of variables—those associated with individual differences in creativity and those associated with information elaboration. Future research may also show that the model has broader implications beyond creativity for team knowledge work.

Chapter 3 From Individual Creativity to Team Creativity: A Meta-Analytic Test of Additive and Disjunctive Aggregation Models and the Moderating Role of Task and Industry Context

Introduction

The rise of the creative economy and creative class in the past decades underscores that creativity is a driving force in contemporary business (Florida, 2002; Howkins, 2001), with organizations that embrace creativity obtaining significantly higher growth rates and profitability. As teams play a pivotal role in acquiring and creating knowledge (Edmondson, 2002; Gibson & Vermeulen, 2002), organizations are increasingly recognizing teams as a key mechanism for creative successes. Such trends are not only evident in technology-oriented businesses, such as SpaceX and Danaher Corp., but also in administrative organizations such as governments worldwide (Puttick, Baeck, & Colligan, 2014). Although it seems intuitive that team creativity requires creative individuals, research has left largely unexplored how individual creativity combines to generate team creativity (van Knippenberg, 2017).

Within the creativity research domain, two aggregation models have been established to understand how individual team member creativity, as a team composition variable, affects team creativity. The model that is most often invoked is the *additive model*, which predicts team creativity from the sum creativity of all team members (Chen, Farh, Campbell-Bush, Wu, & Wu, 2013; Taggar, 2002). This model views team creativity as an additive task (Steiner, 1972) in which each member's creativity contributes to team creativity. By implication, the additive logic sees within-team differences in creativity as less relevant because they average out in predicting team creativity (Humphrey & Aime, 2014). Research has also pointed to an alternative aggregation model that has been less studied: the *disjunctive model*, in which team creativity is understood as a disjunctive task (Steiner, 1972), and predicted by the creativity of the team's most creative member (Gong, Kim, Lee, & Zhu, 2013; Triandis, Bass, Ewen, & Mikesell, 1963). This model emphasizes within-team differences in individual creativity and sees team creativity as driven first and foremost by the team's most creatively capable individual given that creativity is thought of as the "novel minority" over the "ordinary majority" (e.g., Girotra, Terwiesch, Ulrich, & Ulrich, 2010). Obviously, the models overlap somewhat in that, all other things being equal, the higher creativity of the most creative member (i.e., desirable from the point of view of the disjunctive model) implies higher average creativity (i.e., desirable from the point of view of the additive model). These models diverge, however, in their understanding of member differences in creativity, with the disjunctive model favoring a team with higher creativity of the most creative member and lower average creativity over a team with lower creativity of the most creative member and higher average creativity, whereas the additive model would favor the latter over the former.

Conceptually, both additive and disjunctive models have their merits (Sacramento, Dawson, & West, 2008). A review of the evidence base also shows that while both models received support, neither did so consistently. There is evidence supporting the additive model (Chen et al., 2013; Gong, Kim, Lee, & Zhu, 2013; Somech & Drach-Zahavy, 2013), but also evidence failing to support it (Hanke, 2006; Kurtzberg, 2000). Similarly, the disjunctive model has received support (Pirola-Merlo & Mann, 2004; Triandis et al., 1963), but there are also cases in which the model was not supported (Kurtzberg, 2000; Taggar, 2001). Such inconsistent findings suggest that a fruitful way forward is to examine the moderators of the predictive values of the additive and the disjunctive models. A focus on moderation is also consistent with the current state of the science in the study of individual creativity, in which it is widely acknowledged that the influence of personal characteristics predicting creativity is moderated by contextual influences (van Knippenberg & Hirst, 2015; Zhou & Hoever, 2014). A meta-analysis is a particularly powerful way to integrate the available research evidence and identify moderators (Hunter & Schmidt, 2004), and this is the approach we adopted to study the contingencies of the additive and the disjunctive models of team creativity.

The additive and disjunctive models hail from Steiner's (1972) task taxonomy, which captures how the nature of the task determines which aggregation model is more appropriate in predicting team performance. From this, we may rephrase the question of what moderates the predictive power of the additive and the disjunctive models and ask which factors govern the extent to which team creativity is an additive or a disjunctive task. As we outline in the following section, we propose that the answer to this question lies in the standards for creativity in the task context; we propose that the higher the bar is for creative performance, the more individual creativity is needed to make a substantive contribution. Accordingly, we propose that the higher the bar is for creative performance, the more predictive the disjunctive model is and the less predictive the additive model is. Such creative demands are not only manifested in how work tasks require and drive teams in the form of task objectives and instructions (Locke & Latham, 2013; Shalley, 1991), but are also reflected in the industrial patterns in terms of the extent to which creativity is recognized and involved in team activities (Csikszentmihalyi, 1999; Curral, Forrester, Dawson, & West, 2001). Therefore, in order to capture the extent to which teams operate in creativity-demanding environments, we focus on two indicators: creativity task demands (high vs. low) and industrial backgrounds (high-tech vs. low-tech, arguing that high-tech contexts imply higher standards for team creativity). We propose that the additive model is more predictive of team creativity under conditions of low creativity task demands (in low-tech industries) than under conditions of high creativity task demands (in high-tech industries); *vice versa* we propose that the disjunctive model is more predictive with high creativity demands (in high-tech industries).

There is a tendency to see the additive model of aggregating member contributions as the default in team research, and arguably this does not do justice to alternative aggregation models (Chan, 1998; Kozlowski & Klein, 2000). Team creativity research is illustrative of this more general trend with a dominant focus on the additive model and little consideration of the disjunctive model as the one other conceptually plausible model. Presumably, as a consequence, there is as yet no real recognition in team creativity research that the evidence for the additive and the disjunctive models is inconsistent and begs for a moderator analysis (cf. van Knippenberg, 2017). Hence, the contribution of the present study is to bring this issue to the forefront and address it with the powerful evidence of a meta-analysis. In doing so, we not only advance our understanding of the role of individual creativity in team creativity but also develop a theory about the role of the task context in team creativity (cf. Chen, Williamson, & Zhou, 2012). As a secondary contribution, our study also extends an invitation to team performance research outside the creativity domain to consider the contingencies of relevant aggregation models (cf. Humphrey & Aime, 2014; Mathieu, Tannenbaum, Donsbach, & Alliger, 2014).

Theory and Hypotheses

From Individual Creativity to Team Creativity

Team creativity is defined as the generation of novelty and usefulness in work teams (George, 2007; Paulus & Nijstad, 2003). It is similar to individual creativity, as both capture the unitary process of integrating novelty and viability in products, services, and solutions. The fundamental distinction between the two concepts, however, lies in the different levels of analysis: team creativity originates from the congregation of creative resources from individual members. The prerequisite condition for teams to produce collective outcomes is that team members must assemble sufficient creative resources. As individual creativity reflects a stable ability to generate valuable resources for creative tasks (Amabile, 1988; Gough, 1979; Staw, 2009), it is arguably the most relevant disposition to the team repository of creative resources. This naturally raises a question: how does individual creativity combine to develop team creativity?

Despite the theoretical significance of this question, it has received insufficient attention from existing research. In contrast to more extensive investigations of how team creativity emerges from less intuitive predictors such as the Big-5 personality characteristics (e.g., Tadmor, Satterstrom, Jang, & Polzer, 2012; Taggar, 2002), cognitive styles (e.g., Kurtzberg, 2005), regulatory focus (e.g., Sacramento, Fay, & West, 2013), and cultural background (e.g., Martins & Shalley, 2011), empirical studies of the relation between team creativity and individual creativity are neither sufficient nor comprehensive. In our literature review on team creativity, only 29 studies incorporated creativity measures on both the team and individual levels. Of these studies, less than half (48%) tested the composition model of team creativity from individual creativity (see Figure 3). More importantly, these studies mainly examined one composition model (Chen, Farh, Campbell-Bush, Wu, & Wu, 2013; Chiang & Hung, 2014; Gong et al., 2013; for a literature review see Appendix A), thus largely leaving the complexity of team composition (Chan, 1998; Klein & Kozlowski, 2000; Steiner, 1972).

The complexity of team composition is reflected in the presence of multiple aggregation models across various cross-level frameworks (Chan, 1998; Kozlowski & Klein, 2000; Steiner, 1972). Several composition models may apply to the same team construct under different conditions (Chan, 1998). For instance, in Steiner's (1972) taxonomy, team performance can be explained by either the *additive model* of average individual performance, the *disjunctive model* of highest individual performance, or the *conjunctive model* of lowest individual performance under different circumstances. The conjunctive model that underlies the role of the weakest member in teams clearly opposes the nature of positive deviance in the definition of team creativity and has been rejected in prior studies (Pirola-Merlo & Mann, 2004; Triandis et al., 1963). However, both the additive model and disjunctive model, have been independently tested in predicting team creativity and yielded inconsistent evidence. For example, Taggar (2001) investigated 94 course teams and found that only the additive model explains team creative performance. Yet in Pirola-merlo & Mann's (2004) study of 54 R&D teams across industry backgrounds, both the additive model and the disjunctive model share a similar predictive power of team creativity. This leaves us with questions related to the appropriate theoretical conceptualizations of team creativity as an additive or a disjunctive task.

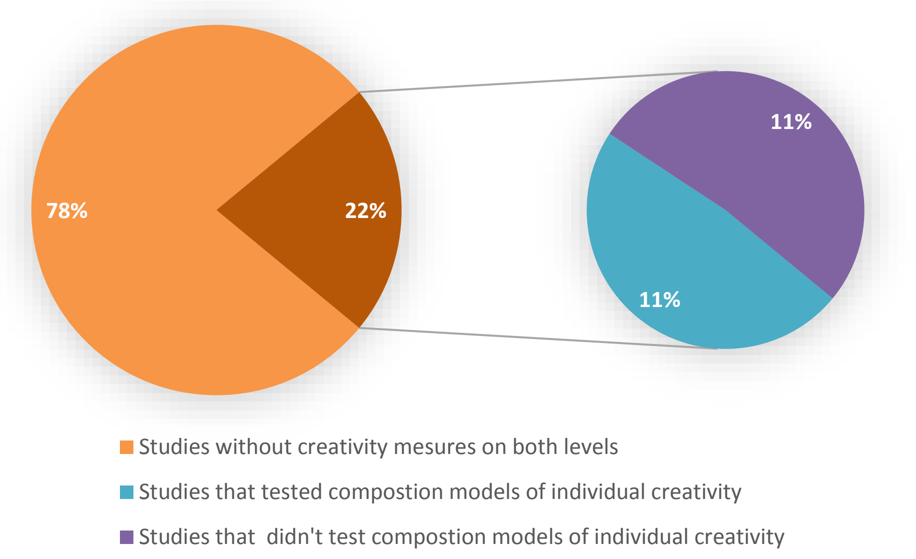

Figure 3. Distribution Chart of Team Creativity Studies on the Aggregation Models

The Additive Model of Team Creativity

The additive model and the disjunctive model are models of how team performance follows from individual contributions. In the context of team creativity, individual creativity implies possession of intrapersonal resources that are valued in the team creative processes, such as novel ideas and creative skills (Amabile, 1988; Staw, 2009; Taggar, 2001). Such creative resources could all potentially contribute to a team's creative outcomes. The additive model is widely applied in many team constructs, and it is also the model that is most applied in studying how team member creativity predicts overall team creativity. The additive model of team creativity implies that creative contributions from all members contribute to team creativity. This is not to deny that some members may be more creative than others, but it does imply that less creative contributions may still add to team creativity in the face of more creative contributions. A strong example of how such an additive model would play out is in idea generation (brainstorming) where team creativity is understood in terms of the volume of ideas generated (i.e., teams that generate more ideas are more creative; Brown, Tumeo, Larey, & Paulus, 1998; Paulus, 2000). Aside from the overlap between the ideas individuals contribute, the task is additive because all contributions, whether more and less creative, add to the overall team creative product. Taking a step away from the brainstorming paradigm to tasks in which teams focus on generating and developing a single creative solution to organizational problems, the additive model would hold that more creative and less creative contributions are combined to generate a team creative product, and the less creative contributions also add to the overall creativity of the team product (e.g., minor tweaks or add-ons to a creative idea). Examples set aside, the additive model would hold that all team creativity is largely an additive task in which team creativity benefits from the creative contributions of all members, or at least that all creative tasks have additive elements where all members can add to the overall team creativity.

As we noted above, there is evidence to support the additive model (Chen et al., 2013; Goncalo & Duguid, 2012; Gong et al., 2013; Taggar, 2001), but also a lack of support that invites the consideration of moderation (Hanke, 2006; Kurtzberg, 2000). We will turn to the consideration of moderation in due course, but also posit a main effect hypothesis for formal testing based on the conceptual consideration that all creative task may have at least additive elements.

Hypothesis 1: The average individual creativity in a team positively relates to team creative performance.

The Disjunctive Model of Team Creativity

There is a longstanding tradition in creativity research to see individual creativity as driven by the creative abilities and dispositions of the individual—that is, to see some individuals as more able to generate creative outcomes than others (van Knippenberg & Hirst, 2015; Zhou & Hoever, 2014). In this sense, the disjunctive model is aligned with this perspective in emphasizing the highest level of individual creativity as the driver for team creativity. Implied in the disjunctive model is that less creative contributions do not substantially add to the most creative contribution. The contribution of other members to team creativity would then not so much lie in their creative contributions as in other contributions to the development of the creative idea (e.g., background research, building prototypes, running tests, etc.). Examples of such disjunctive creative tasks would be breakthrough innovations driven by the creative insights of one "star" member, such as in examples in the popular press of how Pokémon Go, probably the most groundbreaking mobile game in 2016, was a collective product that revolved around the creative ideas of its founder John Hanke (Johnson, 2016).

The disjunctive model has received markedly less attention than the additive model. One reason for this may be that, in essence, the disjunctive model holds that for team creativity, the creativity of only one person—the most creative member—matters. As a result, the model may not fit well with team researchers' intuitions that it is the combination of all members' contributions that lies at the core of teamwork (and indeed, the evidence points to the importance of team process in team creativity, first and foremost information integration; van Knippenberg, 2017). Importantly, however, what is under consideration here is how the *creativity* of individual team members relates to team creativity, and (pure idea generation tasks set aside) we cannot reduce team creativity to creative contributions alone. The notion that it is the most creative member's creativity that is the primary driver of team creativity does not imply that other contributions to the team task do not matter. Instead, it only implies that the *creativity* of these contributions is inconsequential. Thus, the disjunctive model of team creativity is not at odds with the notion that a team creative product is the outcome of teamwork—it only suggests that the *creativity* of that product is driven by the creativity of the team's most creative member.

The core logic of the disjunctive model is that team creativity is primarily driven by the most creative member's creative ideas and that less creative members cannot add to the creativity of the most creative ideas advanced by the most creative member. In a more modest form, the disjunctive model would hold that all creative tasks have, at a minimum, a disjunctive element, where the creativity of the most creative member can bring the team's creativity to a level that less creative members are unable to achieve. As we noted above, the disjunctive model has also received empirical support (e.g., Gong et al., 2013; Pirola-Merlo & Mann, 2004; Triandis et al., 1963), and that there are findings of no support for the disjunctive model as well that ask for a consideration of moderation (Kurtzberg, 2000; Taggar, 2001). We consider moderation next, but posit a main effect hypothesis for formal testing based on the conceptual consideration that all creative tasks may have at least disjunctive elements.

Hypothesis 2: The highest individual creativity positively relates to team creative performance.

Creativity-Demanding Contexts: Moderators of the Additive and Disjunctive Models

As stated in the previous section, considering the extent to which the additive model and the disjunctive model of team creativity hold true also considers the extent to which team creativity is an additive or a disjunctive task (cf. Steiner, 1972). In considering moderation of the predictive validity of the additive and the disjunctive model, we are thus considering task characteristics or proxies of such characteristics. We propose that the key issue here is how high the standards for creativity are: the higher the creative demands for the team products (or put differently, the more the performance goal demands high creativity), the more influential individuals' abilities to generate highly creative contributions would be and the more the disjunctive model rather than the additive model should hold. For some tasks, the issue may be the extent to which team members engage in creative efforts. Examples are idea generation settings, where the quantity of ideas is the explicit performance goal, or in settings like a costume agency where the issue is more the frequency of engaging in creative problem-solving than the radicalness of creative ideas (e.g., Hirst, Van Knippenberg, Chen, & Sacramento, 2011). For other tasks, such as high-tech R&D, the issue is probably much more the search for one or a few highly creative ideas than the frequency with which team members make creative contributions. In settings like the former, the additive model should be a relatively powerful predictor because all creative contributions from team members add to overall team creativity. In settings like the latter, the disjunctive model is likely to be a relatively powerful predictor because the ability to make highly creative contributions is more important than the volume of creative contributions.

In our meta-analysis, we captured and operationalized these notions in two ways: creativity task demands inspired by a more micro perspective, and high-tech versus low-tech industry inspired by a more macro perspective. We see these two factors as complementary ways of getting at the underlying issue—the extent to which the contexts demand highly creative outcomes. The reason to take both approaches is tied to the reality of a meta-analysis that some coding is only possible for some studies (e.g., only field studies can be coded for industry) and the information available from studies may make accurate coding for some factors easier than for others. We thus see our focus on creativity task demands and industry as two complementary ways of getting at the same underlying issue and expect results for both analyses to converge, even when the coding for both factors is expected to only moderately overlap (e.g., because task demands but not industry can be coded for lab experiments and student samples).

Creativity task demands. Without question, team tasks differ in the extent to which they demand creativity. Indeed, there are many team tasks that do not explicitly require creativity. While such tasks can benefit from creativity, there is no strong expectation for the team to be creative and, to a certain extent, team creativity may reflect the extent to which the team engages in creative efforts at all. In such settings, it does not take very creative contributions to add to team creativity, and creative contributions from all team members may contribute to team creativity. The fact that creativity is not a task demand may even discourage more radical creativity because more radically creative ideas can be perceived as deviating too much from what the team is supposed to focus on (cf. the notion of normative expectations as, for instance, captured by team climate; Glisson & James, 2002). Moreover, when a more modestly creative idea already makes a contribution, team members may feel less pressure to invest in more radically creative contributions (cf. satisficing; Simon, 1979, and the notion of the greater motivating potential of more challenging goals; Locke & Latham, 2013). In such situations, team creativity arguably has strong additive elements, and contributions from all members may add to team creativity.

Conversely, other team tasks explicitly require creativity, and can moreover explicitly demand high levels of creativity, for instance in R&D attempts to realize more radically innovative products (Leifer et al., 2002). When creativity demands are high, this can be expected to have both the goal-setting effect of more challenging creativity goals stimulating more creative efforts (e.g., Curral, Forrester, Dawson, & West, 2001) and the more group-normative climate effect of rendering members less hesitant to share more radically creative contributions (Chua & Iyengar, 2008; Harrington, 1975; Shalley, 1991). Such a creativity-focused setting encourages team members to develop and advance radical ideas that would otherwise remain undeveloped or be suppressed due to their deviation from people's understanding of their task requirements (Alexander & van Knippenberg, 2014; Runco, 2003). It is important to note that this also means that individuals' abilities to generate highly creative contributions are also more of a factor than with lower creativity demands. In other words, when creativity demands are higher, the task gains more of a disjunctive element and the creativity of the team's most creative member becomes more predictive of team creativity.

Hence, we propose:

Hypothesis 3a: Creativity task demands moderate the relationship between average individual creativity and team creativity, such that average individual creativity has a stronger relationship with team creativity in team tasks with low creativity demands compared with high creativity demands.

Hypothesis 3b: Creativity task demands moderates the relationship between the highest individual creativity and team creativity, such that the highest individual creativity has a stronger relationship with team creativity in team tasks with high creativity demands compared with low creativity demands.

Industrial backgrounds. A complementary way of capturing the extent to which teams work in a context emphasizing creativity is to look at industrial requirements (Amabile, Conti, Coon, Lazenby, & Herron, 1996; Curral et al., 2001; Mathieu, Maynard, Rapp, & Gilson, 2008). Industrial environment is an important yet often neglected restraint on team creativity. In Csikszentmihalyi's (1997) system view of creativity, each domain/industry has its creative paradigm that delimits social expectations of creative activities and behavioral patterns. R&D teams in the IT industry, for example, are more likely to engage in creative processes of identifying problems, contradicting normal solutions, formulating and testing hypotheses than manufactural teams in the tobacco industry.

Thus, the second approach we propose to capture the moderating role of creativity-demanding contexts is a focus on the industrial backgrounds in which the team operates. Creativity occurs across industries (Woodman, Sawyer, & Griffin, 1993), and the macro environment composes an important element in the work environment of team creativity (Amabile et al., 1996). Industrial influences have been recognized in meta-analyses focusing on other team composition issues (Bell, 2007; Devine & Philips, 2001; Joshi & Roh, 2009), but not in team creativity research. Industrial backgrounds specify the behavioral patterns of creativity activities in a given domain (Mowery & Rosenberg, 1979). As indicated in creativity literature, engaging in creative activities activates creative mindsets to express and embrace radical ideas that are usually too risky to be pursued (Gilson & Shalley, 2004; Zhang & Bartol, 2010). For instance, high-tech industries feature intensive involvement of complex technology and skills, R&D activities, rapid product cycles, and fast growth (Klette & Kortum, 2004). Creativity activities involve formulating hypotheses, linking ideas from diverse sources, and contradicting traditional solutions are core practices in these industries. Work teams thus naturally engage in creativity behaviorally, cognitively, and emotionally while devoting more attention to highly creative inputs than those in other industries such as manufacturing and food industries.

We therefore examine two categories of industrial backgrounds: *high-technology industries* that involve intensive creativity-related activities, such as computer engineering and pharmaceutical industries, and *low-technology industries* that involve less intensive creativity-related activities, such as health care and manufacturing industries. On the basis of the available evidence we also include a third category that does not really concern industry, namely student samples, which include both lab experiments and student teamwork in university courses/lectures. Conceptually, this third category is not part of our hypothesis, but inclusion in the analysis allows for this information to be included in the results for interested readers.

Following from our logic as outlined in the previous section, we propose that the additive model has a stronger predictive power in low-tech industries than in high-tech industries, whereas the predictive power of the disjunctive model is stronger in high-tech than in low-tech industries. High-tech industries represent more creativity-demanding environments, both in terms of more explicit expectations for creativity as part of the job and in terms of a higher bar for creative contributions to be considered valuable. In high-tech industries, the push to generate highly creative outcomes can thus be expected to give rise to an environment in which individuals' ability to generate highly creative ideas is an important influence. Accordingly, the disjunctive model should be quite applicable in such industries. The additive model would be less predictive, however, because in high-tech industries it will be relatively difficult for a less creative idea to substantially contribute to team creativity. In low-tech industries in contrast, the push for creativity and the level at which creativity is expected will typically be lower. With this lower bar in place, the additive model is more likely to apply, and the disjunctive model is less likely to apply. In sum:

Hypothesis 4a: The industrial background moderates the relationship between average individual creativity and team creativity, such that average individual creativity has a stronger relationship with team creativity in low-tech industries than in high-tech industries.

Hypothesis 4b: Industrial background moderates the relationship between the highest individual creativity and team creativity, such that the highest individual creativity has a stronger relationship with team creativity in high-tech industries than in low-tech industries.

Method

Literature Search

We searched several databases (i.e., Web of Science, PsycINFO, EBSCO, ABI/INFORM, ProQuest Dissertation) for empirical studies on team creativity and team innovation between 1980 and September 2015. In our keyword search, we combined the keywords team, group, collective, and collaborative with creativity and innovation to ensure a comprehensive coverage (cf. Devine & Philips, 2001). We then scrutinized the reference lists of the prior meta-analysis (Hülsheger, Anderson, & Salgado, 2009). This identified more than 3000 journal articles, conference papers, and doctoral dissertations.

Inclusion Criteria

Studies were included if they: (a) measured team creative/innovative outcomes; (b) included measures of individual creativity (i.e., average creative performance, highest creative performance, creative personality); and (c) provided sufficient statistical information to compute effect sizes. Given that the statistics of interest were not always reported in the studies, we emailed the authors of several studies for additional statistics. This criterion generated 125 articles/dissertations/manuscripts on team creativity and innovation. Among these, 29 effect sizes from 28 studies, including both individual creativity and team creativity, were identified and coded for the present meta-analysis.

Dataset and Coding Schemes

Initially, one author examined the studies twice for sample size, correlation, and statistical artifact information, such as the reliability of used measures. Then, another author independently coded a random sample of approximately 10% of the 125 articles (13 out of 125 articles) to confirm the number of relevant effect sizes (i.e., 29 effect sizes from 28 studies) and to check the reliability of coding. Interrater agreement was 96% percent for these articles. We resolved the discrepancies by jointly checking against the original documents to reach consensus.

We developed a coding scheme for relevant effect sizes and artifact information. First, we coded both creativity and innovation for the outcome variable, as both concepts capture the same essence of novelty and usefulness (Amabile, 1996; Anderson, Potocnik, & Zhou, 2014). For studies of multiple ratings (e.g., team members vs. team leaders vs. external experts) and those of different dimensions of creativity/innovation (e.g., novelty and usefulness; quality and quantity; originality and fluency), we calculated the composite correlation scores with Hunter and Schmidt's (2004) formula. This was to ensure the independence of effect sizes (Hunter & Schmidt, 2004). In contrast, studies of independent samples were treated as multiple studies and coded separately.

The coding scheme for our moderators—creativity task demands and industrial backgrounds—was developed by the authors and then applied to sampled studies by the first author. Creativity task demands (high vs. low) refer to the extent to which teams are explicitly instructed to express creativity in order to accomplish tasks. We coded this variable from both explicit reports on task characteristics and relevant measures as a proxy.

This is because although almost all experimental studies reported the instruction lines and procedures of team tasks in detail, field studies often provided little information about team tasks, but reported relevant measures of task environment instead, such as support for innovation/creativity (Chen et al., 2013), creative climate (Gong et al., 2013), environmental demand (Chiang & Hung, 2014), novelty in jobs (Vera, 2002), task adherence to standard (Miron-Spektor, Erez, & Naveh, 2011), and job demand (Sacramento et al., 2013). We hence used these to indicate the creativity demand in team tasks. Notably, object design tasks and different versions of alternative usage tasks were coded as high-demand tasks (Bissola, Imperatori, & Colonel, 2014; Goncalo & Duguid, 2012), whereas problem-solving tasks or resolving in-class puzzles were coded as low-demand tasks (Taggar, 2002). Given that different Likert scales were deployed in sampled studies, we transformed all scores into a percentage whereby coded studies scoring higher than 50% were classified to the high-demand condition, and those equal to or lower than 50% to the low-demand condition.

The other moderator—industrial backgrounds (high-tech industries vs. low-tech industries vs. student samples)—was coded according to the intensity of the creativity-related activities involved, such as R&D activities in a given industry. We relied on two criteria to classify sampled industries: a) the longstanding definition of high-technology industries in strategy and innovation literature (Schilling & Phelps, 2007), and b) the industrial taxonomy presented in the OECD (Organization for Economic Co-operation and Development) Directorate for Science, Technology and Industry (2011). High-tech industries refer to those involving intensive creativity-related (R&D) activities, such as telecommunication, microelectronics, and defense industries. Teams in these industries often face most challenging markets and customer needs and tend to invent state-of-the-art solutions. In contrast, low-tech industries involve less intensive creativity-related activities, such as public administration, nursing, and banking. Teams in this category face more conventional and less challenging markets and customers, and tend to focus on adaptive solutions. Noticeably, studies using mixed samples from various industries were also coded under this category. The last category is student samples, which represents student samples from educational institutions. Teams in this category do not confront much risk for team performance, and also receive little reward for creative expressions besides course credits or quick money for participation.

Meta-Analytic Procedures

We adopted the Schmidt-Hunter psychometric meta-analysis method for our analyses (Hunter & Schmidt, 2004). This method is built on a random model estimation, which attributes the differences to sampling errors, study artifacts, and remaining unmeasured random components. Findings from the random model are thus more conservative than those from its counterpart, the fixed model, which attributes homogeneous studies and attributes variances across studies only to sampling errors and other artifacts (Lipsey & Wilson, 2001). For each study, we first corrected all effect sizes for sampling errors, and then corrected the artifacts (measurement errors and range restrictions) in independent variables and dependent variables using Cronbach's alpha coefficients provided in the studies. Studies that did not report Cronbach's alpha coefficients were assigned the average coefficient value from the other studies in our analysis (cf. Miron-Spektor et al., 2011). In addition, we assigned a reliability coefficient of 1.00 to objective measures, following the routine in prior meta-analytic research (de Wit, Greer, & Jehn, 2012; Riketta, 2008).

To test the significance of our main effects and categorical moderation effects, we performed meta-analysis in a Microsoft Excel spreadsheet that applied the Schmidt-Hunter psychometric meta-analysis method (De Jong, Dirks, Jansen, & Bal, 2012; de Wit et al., 2012). We compared the 90% CIs of corresponding moderator categories. If the CI ranges did not overlap between categories, we interpreted that as reliable differences among categories (Hunter & Schmidt, 2004). We adopted an SPSS macro to test the impact of continuous moderators in a meta-analytic weighted least squares (WLS) regressions (Field & Gillett, 2010).

In the following section, we present the effect size distributions of both the uncorrected (r, SD_r) and corrected (ρ, SD_ρ) estimates on each population correlation. First, we present the number of studies included in determining the correlation (k) and the total number of teams in the studies (n) for each population correlation. Then, 90% credibility interval (CV) for each population correlation is shown for the generalizability information, and 90% confidence interval (CI) around each population correlation estimate is reported for the precision of effect size estimates (Hunter & Schmidt, 2004).

Results

Table 4 presents the overall results of hypothesized effects. In support of Hypothesis 1 and 2, we found medium effect sizes on both the average individual creativity (i.e., the additive model, ρ = .32, 90% CI = [.19, .36]), and the highest individual creativity (i.e., the disjunctive model, ρ = .26, 90% CI = [.14, .30]). The difference between the two models is not significant ($r1$ = .32, $r2$ = .26, 90% asym CIs $r1$-$r2$ = [-0.06, 0.17]; Zou, 2007). Nevertheless, the predictive power of the disjunctive model is more stable than that of the additive model, as 90% credibility intervals include zero on the additive model (90% CV = [-.06, .70]), but not on the disjunctive model (90% CV = [.00, .53]). The implication is that the disjunctive model is valid across different situations, whereas the effect of the additive model is subject to undisclosed moderators.

To compare the correlations across different conditions proposed in our moderation hypotheses (Hypotheses 3a, 3b, 4a, and 4b), we followed Zou's (2007) approach to construct a Confidence Interval for the differences between the CIs of individual correlations. We found that the additive model is more predictive in teams with low creativity task demands (ρ = .48, 90% CI = [.29, .52]) than in teams with high creativity task demands (ρ = .23, 90% CI = [.10, .31]). The difference is significant (*r1* = .48, *r2* = .23, 90% asym CIs *r1-r2* = [.04, .35]). On the other hand, the disjunctive model has the same predicting power in low-demand condition (ρ = .26, 90% CI = [.10, .33]) as in high-demand condition (ρ = .26, 90% CI = [.11, .33]). The difference between them is insignificant (*r1* = .26, *r2* = .26, 90% asym CIs *r1-r2* = [-.15, .16]). Thus, Hypothesis 3a is supported, while Hypothesis 3b is rejected.

Results further reveal that the additive model has its largest effect size in low-tech industries (ρ = .46, 90% CI = [.26, .52]), followed by student samples (ρ = .25, 90% CI = [.07, .36]), and high-tech industries (ρ = .20, 90% CI = [.09, .27]). The effect size in low-tech industries is significantly higher than that in high-tech industries (*r1* = .46, *r2* = .20, 90% asym CIs *r1-r2* = [.05, .37]), supporting Hypothesis 4a. Not related to hypothesis testing, the predictive power of the additive model in student samples did not differ from that in low-tech industries (*r1* = .25, *r2* = .46, 90% asym CIs *r1-r2* = [-.37, .02]), nor from that in high-tech industries (*r1* = .25, *r2* = .20, 90% asym CIs *r1-r2* = [-.21, .13]).

For the disjunctive model, the effect size was higher in high-tech industries (ρ = .40, 90% CI = [.12, .60]) than in low-tech industries (ρ = .27, 90% CI = [.14, .32]), but the difference was not significant (*r1* = .40, *r2* = .27, 90% asym CIs *r1-r2* = [-.13, .38]). Even when the pattern of effect sizes was in line with Hypothesis 4b, Hypothesis 4b was thus not supported. While unrelated to hypothesis testing, we further note that the predictive power of the disjunctive model in high-tech industries did not differ from that in student samples

(ρ = .17, 90% CI = [.03, .25]), as the difference was not significant (*r1* = .40, *r*2 = .17, 90% asym CIs *r1*-*r2* = [-.48, .05]), nor did the disjunctive model's predictive power differ between low-tech industries and student samples (*r1* = .27, *r2* = .17, 90% asym CIs *r1*-*r2* = [-.24, .05]).

Table 4. Meta-Analytic Results of All Hypotheses

Predictors	*k*	*N*	ρ	SD_ρ	90% CVs	*r*	SD_r	*SE*	90% CIs	Critical ratio Z	90% CIs r1-r2	90% asym CIs r1-r2	Fail Safe N
Individual Creativity (Hypothesis 1 & 2)													
Average individual creativity	27	1,931	0.32	0.23	-0.06, 0.70	0.28	0.22	0.05	0.19, 0.36	1.02	[-0.06, 0.17]	[-0.06, 0.17]	59
Highest individual creativity	20	1,842	0.26	0.16	0.00, 0.53	0.22	0.17	0.05	0.14, 0.30				33
Creativity demand (Additive Model, Hypothesis 3a)													
High creativity demand	15	1,237	0.23	0.21	-0.11, 0.58	0.21	0.21	0.06	0.10, 0.31	-2.58	[-0.35, -0.04]	[-0.35, -0.04]	21
Low creativity demand	12	694	0.48	0.20	0.15, 0.81	0.40	0.19	0.07	0.29, 0.52				46
Creativity demand (Disjunctive Model, Hypothesis 3b)													
High creativity demand	12	1,149	0.26	0.18	-0.04, 0.57	0.22	0.18	0.07	0.11, 0.33	0.06	[-0.15, 0.16]	[-0.15, 0.16]	20
Low creativity demand	8	693	0.26	0.12	0.07, 0.45	0.22	0.16	0.07	0.10, 0.33				13

Predictors	*k*	*N*	*ρ*	SD_ρ	90% CVs	*r*	SD_r	*SE*	90% CIs	Critical ratio Z	90% CIs r1-r2	90% asym CIs r1-r2	Fail Safe N
Industrial backgrounds (Additive Model, Hypothesis 4a)													
High-tech industries	6	335	0.20	0.00	0.20, 0.20	0.18	0.12	0.06	0.09, 0.27	-2.63	[-0.37, -0.05]	[-0.37, -0.05]	7
Low-tech industries	12	780	0.46	0.24	0.05, 0.86	0.39	0.22	0.08	0.26, 0.52	1.83	[-0.02, 0.37]	[-0.02, 0.37]	43
Student samples	9	777	0.25	0.23	-0.13, 0.62	0.22	0.21	0.09	0.07, 0.36	-0.46	[-0.21, 0.13]	[-0.21, 0.13]	14
Industrial backgrounds (Disjunctive Model, Hypothesis 4b)													
High-tech industries	5	335	0.40	0.29	-0.09, 0.88	0.36	0.25	0.15	0.12, 0.60	1.02	[-0.13, 0.38]	[-0.13, 0.38]	15
Low-tech industries	9	819	0.27	0.09	0.12, 0.43	0.23	0.14	0.06	0.14, 0.32	1.33	[-0.05, 0.24]	[-0.05, 0.24]	16
Student samples	6	688	0.17	0.08	0.03, 0.31	0.14	0.12	0.07	0.03, 0.25	1.75	[-0.05, 0.48]	[-0.05, 0.48]	5

Note. *k* = number of correlations; *n* = total sample size; *ρ* = estimated true correlation (fully corrected for artifacts); SD_ρ = Standard deviation of true correlation; *r*= sample size weighted mean observed correlation; SD_r = Sample size weighted observed standard deviations of correlations; CVs = Credibility Intervals; CIs = Confidence Intervals.

Supplementary Analysis

In addition to our hypothesis tests, we also explored potential methodological moderating influences that were included in our data gathering efforts: team size; publication bias (published vs. unpublished); measurement of team creativity (internal rating offered by team members and direct leaders vs. external rating by external judges or objective indicators), and common source bias. Considering the continuous nature of team size, we analyzed its moderating role on the additive and disjunctive models of team creativity in meta-analytic weighted least squares (WLS) regressions (Field & Gillett, 2010). The results did not support the moderating role of team size on the relationship between the average individual creativity and team creativity, with a non-significant interaction term ($\rho = -.01$, $t = -.67$, $p > .1$, 95% CI = [-.05, .03]). The moderating role of team size on the relationship between the highest individual creativity and team creativity was also not supported, with a non-significant interaction term ($\rho = -.18$, $t = -.99$, $p > .1$, 95% CI = [-.06, .02]).

The moderating effects of the three categorical moderators—publication bias, measurement of team creativity, and common source bias—were analyzed in the Microsoft Excel spreadsheet that applied the Schmidt-Hunter psychometric meta-analysis method (De Jong et al., 2012; de Wit et al., 2012). as shown in Table 5, we found no difference between the effect sizes of published studies and unpublished studies for the additive model ($r1 = .38$, 90% CI = [.24, .42], $r2 = .24$, 90% CI = [.05, .40], 90% asym CIs $r1$-$r2$ = [-.09, .30]), or for the disjunctive model ($r1 = .36$, 90% CI = [.19, .42], $r2 = .29$, 90% CI = [.14, .37], 90% asym CIs $r1$-$r2$ = [-.11, .21]). As to the moderating effect of common source bias, no difference was found between the effect sizes of common sourced studies and differed sourced studies for the additive model ($r1 = .41$, 90% CI = [.24, .45], $r2 = .22$, 90% CI =

[.09, .31], 90% asym CIs $r1$-$r2$ = [-.01, .30]), or for the disjunctive model ($r1$ = .39, 90% CI = [.18, .48], $r2$ = .29, 90% CI = [.16, .33], 90% asym CIs $r1$-$r2$ = [-.08, .26]). Measurement of team creativity (internal vs. external) was found to moderate the predictive power of the additive model, such that the effect size is higher in studies of internal ratings than those of external ratings ($r1$ = .45, 90% CI = [.27, .51], $r2$ = .24, 90% CI = [.10, .33], 90% asym CIs $r1$-$r2$ = [.01, .33]). This moderator, however, does not influence the predictive power of the disjunctive model ($r1$ = .32, 90% CI = [.19, .38], $r2$ = .35, 90% CI = [.15, .44], 90% asym CIs $r1$-$r2$ = [-.18, .16]).

Table 5. Meta-Analytic Results of Supplementary Analyses

Predictors	*k*	*N*	ρ	SD_ρ	90% CVs	*r*	SD_r	*SE*	90% CIs	Critical ratio Z	90% CIs r1-r2	90% asym CIs r1-r2	Fail Safe N
Publication bias (Additive Model)													
Published	18	1,222	0.38	0.19	[.06, .70]	.33	.19	.06	[.24, .42]	1.07	[-.09, .30]	[-.09, .30]	52
Unpublished	9	613	0.24	0.29	[-.23, .72]	.22	.27	.11	[.05, .40]				13
Publication bias (Disjunctive Model)													
Published	12	875	0.36	0.20	[.03, .70]	0.31	0.19	0.07	[.19, .42]	0.60	[-.11, .21]	[-.11, .21]	32
Unpublished	8	531	0.29	0.14	[.06, .53]	0.26	0.17	0.07	[.14, .37]				16
Common method bias (Additive Model)													
Common sources	14	1,022	0.41	0.20	[.07, .74]	0.35	0.19	0.06	[.24, .45]	1.86	[-.01, .30]	[-.01, .30]	43
Differed sources	13	909	0.22	0.21	[-.12, .57]	0.20	0.21	0.07	[.09, .31]				17
Common method bias (Disjunctive Model)													
Common sources	9	667	0.39	0.24	[-.01, .79]	0.33	0.21	0.09	[.18, .48]	1.07	[-.08, .26]	[-.08, .26]	26
Differed sources	11	739	0.29	0.11	[.11, .46]	0.25	0.15	0.05	[.16, .33]				21

Predictors	***k***	***N***	**ρ**	**SD_ρ**	**90% CVs**	***r***	**SD_r**	***SE***	**90% CIs**	**Critical ratio Z**	**90% CIs r1-r2**	**90% asym CIs r1-r2**	**Fail Safe N**
Measurement of team creativity (Additive Model)													
Internal rating	13	819	0.45	0.22	[.09, .82]	0.39	0.21	0.07	[.27, .51]	2.17	[.01, .33]	[.01, .33]	47
External rating	14	1,016	0.24	0.21	[-.11, .59]	0.21	0.20	0.07	[10, .33]				20
Measurement of team creativity (Disjunctive Model)													
Internal rating	10	702	0.32	0.12	[.13, .51]	0.28	0.14	0.06	[.19, .38]	-0.10	[-.18, .16]	[-.18, .16]	23
External rating	10	704	0.35	0.24	[-.05, .74]	0.29	0.22	0.09	[.15, .44]				25

Note. k = number of correlations; n = total sample size; ρ = estimated true correlation (fully corrected for artifacts); SD_ρ = Standard deviation of true correlation; r= sample size weighted mean observed correlation; SD_r = Sample size weighted observed standard deviations of correlations; CVs = Credibility Intervals; CIs = Confidence Intervals.

Discussion

A fundamental question in team creativity research is how member creativity is related to team creativity. Moving beyond the unspecified intuition that individual creativity is good for team creativity, team creativity research has identified two meaningful aggregation models: the additive model and the disjunctive model. Our meta-analytical integration of the literature shows that overall, both models are moderately related to team creativity. In particular, the additive model and the disjunctive model do not differ significantly in their predictive power. Moving beyond the current state of the science, our analysis also supports the hypothesis that the additive model is more predictive with low creativity task demands and in low-tech industries than with high-creativity task demands and in high-tech industries. Our hypothesis predicting the reverse pattern for the disjunctive model was not supported, with the main conclusion for the disjunctive model being that it is supported across contexts.

Theoretical Implications

Team creativity research had established the validity of the additive and the disjunctive models in understanding the relationship between team member creativity and team creativity. However, it did not follow up on the evidence that neither the additive model nor the disjunctive model is consistently supported by empirical research. This evidence suggests that to advance our understanding of the fundamental relationship between member creativity and team creativity, we need to take the boundary conditions into account. Aggregation models of team performance—including team creativity—are by their very nature contingent on the task and implicit and explicit expectations surrounding task performance (Steiner, 1972). This conceptual linkage is in line with our focus on the contextual demands for creativity. It also points to an important and fundamental insight for team creativity research: team creativity is more of an additive task in some contexts than in others.

Research on team composition and team creativity has recognized that composition (in terms of aspects other than individual creativity) may have effects that are moderated by such factors as psychological safety (Gibson & Gibbs, 2006), team creative confidence (Baer, Oldham, Jacobsohn, & Hollingshead, 2008), and team member perspective taking (Hoever, van Knippenberg, van Ginkel, & Barkema, 2012). The notion that creativity demands may influence the impact of team composition has so far been ignored, however, potentially because creativity as an outcome seems to define the task and does not invite researchers to consider the nature of the creative task. A focus on the additive and disjunctive models invites an explicit consideration of the team's creativity task, and results in the conclusion that team creativity tasks do differ in the extent to which they benefit from the creative contributions of all members.

This insight is important not only because it advances our understanding of the influence of team member creativity on team creativity but also because it can inspire new insights into the influence of other aspects of team composition. As to the first, future research may systematically study factors that reflect the extent to which a team creativity task is additive to more comprehensively capture the influence of contextual demands for creativity. As to the second, some team composition variables would derive their influence on team creativity at least in part from their link to individual creativity (e.g., openness to experience as a personality precursor to creativity; Feist, 1998). The current findings would suggest that an additive model approach to team openness to experience composition makes more sense for some tasks than for others. Obviously, these are issues for future research to address, but in a sense, this is exactly our point: the current insights have the potential to inspire new research that advances our understanding of team composition effects on team creativity.

It is also interesting and important to note that the results support our contingency perspective for the additive model of team creativity, but not for the disjunctive model of team creativity. One interpretation of this is that the support for our contingency perspective for additive tasks but not for disjunctive tasks reflects an asymmetry in the influence of ability. The argument for the disjunctive model revolves around the notion that some individuals cannot produce certain levels of creativity whereas others can. The argument for the additive model revolves around the notion that when the demands for team creativity are lower, all members can contribute to the team's creative outputs. However, the latter argument leaves open the possibility that more creative members would still make more creative contributions. These contributions may influence others on the team both as a source of inspiration and in setting a standard for the level of creativity that is appreciated, accepted, or possible. The disjunctive model may therefore still hold, even for creative tasks with strong additive elements, because of a creativity-motivating influence of a highly creative team member. Obviously, our meta-analysis does not include the data to speak to this post hoc interpretation, and this is something that would have to be substantiated by future research.

Our findings also underscore the value of seriously and systematically investigating the disjunctive logic that has long been largely neglected. This neglect is reflected in the absence of disjunctive hypotheses in studies including empirical tests of the additive model and in instances where relevant evidence for the disjunctive model is treated as in the periphery of less relevant study findings (for a review, see Appendix A). The current evidence shows that the disjunctive model holds over performance contexts and does not differ in its overall relationship with team creativity from the additive model. These findings suggest that the disjunctive model is worth more research attention, including more fine-grained studies to examine its boundary conditions. This would contribute to an understanding of different bottom-up influences from individual creativity to team creativity, and add to our knowledge of creativity as a complex and multilevel phenomenon (Anderson et al., 2014; Shalley, Zhou, & Oldham, 2004).

The evidence for the predictive power of the disjunctive model also suggests that it may be worthwhile to make a distinction between creative and noncreative contributions in team creativity. As we noted in the introduction, the disjunctive model does not imply that team creativity, in the end, is an individual task where the team is merely broad together to increase the chance of highly creative individual contributions emerging. Beyond the unique setting of pure idea generation (brainstorming) tasks where the sole contribution expected is creative ideas, team creativity is a process that requires more than just creative contributions. Depending on the outcome a team is pursuing, creativity may require background research, building prototypes, testing prototypes, etc. These are all important aspect of the team process leading to a team creative outcome but these are also processes that often revolve markedly less around members' creativity and primarily around other members' knowledge skills and abilities. A promising route for developing our understanding of team creativity from a team composition perspective may thus be to explore how creative contributions and other contributions combine to produce team creativity—and it is altogether possible that even when members' creative contributions are best understood to contribute to team creativity as a disjunctive task, other elements of the team processes leading up to team creativity are better understood as additive tasks.

Methodological Implications for Team Creativity Research

This meta-analysis also speaks to some potential methodological concerns in team creativity research, at least where the predictive validity of the additive and disjunctive models is concerned. First, no support was found for the publication bias or the common method bias in relation to either aggregation model. This suggests that multi-source data, although always preferred in empirical studies, does not differ from single-source data in capturing the relation between individual creativity and team creativity (at least not in respect to the additive and disjunctive models).

We did find that the predictive power of the additive model is contingent on the measurement of team creativity: average individual creativity is more predictive of team creativity when team creativity is rated internally (i.e., team members or direct team leaders) rather than externally (i.e., other corporate managers or external experts). No measurement bias was found on the disjunctive model, however. This might be explained by the overrepresentation of internal ratings in the student samples and low-tech industries, as we found a positive correlation between the measurement of team creativity and industrial backgrounds (χ^2 (2, N = 29) = 10.99, p < .01). More specifically, all student samples were rated internally and teams in low-tech industries use more internal ratings than teams in high-tech industries.

Limitations and Future Directions

Like all empirical tests, our study has its limitations. One concern might be its small sample size, which may be associated with second-order sampling error in meta-analytic moderation models (Hunter & Schmidt, 2004). Nevertheless, Fisher's fail-safe *N* values for all tested effect sizes are fairly large (see Table 1 & 2). With the current rate of empirical tests on team creativity and individual creativity-relevant dispositions, it will take at least a decade more of research to overturn our findings here. The reported Fisher's fail-safe *N* values therefore consolidate our findings (Hunter & Schmidt, 2004).

Our coding of two moderators is also not ideal. As reported above, although most studies provided information about sampling background such as location, industries, and demographic compositions, task descriptions are rarely reported in field studies, particularly in studies of mixed samples from various organizations. As a result, we had to use relevant measures of team task environment as a proxy of creativity task demands (cf. Vera, 2002). Although it does affirm the catalytic role of task contexts in developing team creativity, this coding is not perfect. Moreover, due to the lack of macro contextual information, we captured the industrial pattern of creative activities in a general variable of industrial backgrounds, which concerns many aspects of industrial backgrounds. In order to refine our understanding of the contextual impacts from both micro and macro levels, we would welcome empirical studies providing more detailed descriptions of task features, team operations, and organizational environmental features.

Finally, we did not distinguish research on creativity and innovation (cf. van Knippenberg, 2017). To some, the creativity-innovation distinction reflects a focus on idea generation (creativity) versus idea generation and implementation (innovation), and indeed there are creativity studies that are pure idea generation studies. However, as van Knippenberg (2017) outlines, in field research team creativity is typically understood to move beyond idea generation and to include implementation; moreover, innovation measures that try to distinguish idea generation from idea implementation often end up collapsing them into one measure, presumably because idea generation often is only observable through implementation. Accordingly, there seems to be a good case that in practice the overlap between team creativity and team innovation studies is larger than their distinctiveness. Following van Knippenberg (2017), we may also note, however, that whereas the current state of affairs justifies combining team creativity and team innovation studies in one meta-analysis (indeed, Hülsheger et al., 2009), there actually is a conceptual case to dedicate more research attention to the specific challenges of idea implementation, and the current combination of team creativity and team innovation is not to deny this important perspective for future research.

An interesting avenue for future research may also be to develop our understanding further of the kind of creativity involved in the team task. Creativity theories acknowledge the distinction between radical creativity and incremental creativity (Litchfield, 2008; Mumford & Gustafson, 1988). A number of studies have investigated factors that facilitate and/or impair one type of creativity versus the other and have identified various individual and contextual characteristics (e.g., Gilson & Madjar, 2011; Madjar, Greenberg, & Chen, 2011). For instance, having creative coworkers, regardless of the absolute level of the coworkers' creativity, turns to benefit incremental creativity but not radical creativity (Madjar et al., 2011). Yet in the team contexts, how such inputs aggregate to shape incremental and radical creativity differently has been rarely considered. Implied in our analysis is that the disjunctive model applies more for teams seeking more radical creativity, whereas the additive model applies more in contexts of more incremental creativity. To a certain extent our coding in terms of creativity task demands and industrial backgrounds gets to this, but the overlap is not perfect. Idea generation tasks for instance have high creativity demands—creative contributions are the only thing asked from team members—but can in fact be performed with incremental creativity only. Meta-analysis can only test what is codeable, and incremental versus radical creativity seems a bridge too far. Our conceptual analysis suggests, however, that focusing on this distinction may be a natural and consistent extension of the current moderator analysis.

Conclusion

The relationship between individual creativity and team creativity is fundamental to team creativity, and as the current analysis shows, it is more complex than one might image at first blush. It seems obvious that teams are more creative with more creative members, and presumably this notion for many people implies the additive model of aggregating individual to team creativity. The current findings show that the issue is more complicated: whereas the additive model has its predictive validity, it is a stronger predictor in some contexts than in others, and the disjunctive model that emphasizes the creativity of one "star" member rather than of all members has predictive validity too. The current study thus extends a clear invitation to consider the contingencies of the effects of member creativity on team creativity, and to not see this as an additive task issue by default but to also consider the disjunctive logic.

Appendix A

A 3.1 Summary of published empirical studies on the aggregation models of team creativity, 1980—2015

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Bissola et al., (2014)	119 student teams from an undergraduate business course in Italy	Individual creativity rated by team members with Williams's (1993) scale	Team creativity rated by team members with O'Quin and Besemer's (2006) scale	Did not test any composition models, but reported a positive correlation between individual creativity and team creativity (insignificant)	No	No
Černe, Jaklič, & Škerlavaj, (2013)	23 work teams from a Slovenian manufacturing and processing company	Individual creativity rated by team members themselves with Zhou & George's (2001) scale	Team innovation rated by team leaders with Lovelace, Shapiro, & Weingart's (2001) scale	Did not test any composition models, but reported a positive correlation between average individual creativity and team innovation (significant)	No	No
Chen et al., (2013)	95 research and development (R&D) project teams from 37 firms across diverse industries (e.g., aeronautical and telecommunication) in China	Individual innovative performance rated by team leaders with Janssen's (2000) scale	Team innovation rated by external managers with De Dreu's (2002) scale	Tested the relationship between average individual innovation and team innovation, and supported the mediating role of average individual innovation on the relationship between team support for creative climate and team innovation	Yes	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Chiang & Hung, (2014)	83 teams from electronic product manufacturers listed as members of the Taiwanese Electrical and Electronics Manufacturers Association in Taiwan	Individual creativity rated by team leaders with Farmer, Tierney, & Kung-McIntyre's (2003) scale	Team innovation rated by external marketing managers with Moorman & Miner's (1997) scale	Tested and supported a positive relationship between the average individual creativity and team innovation	Yes	No
Gilson, (2002)	47 work teams from a larger regional bank and a graphic design company in United States.	Individual innovativeness rated by team members with a scale adapted from West (1987) and Burningham & West (1995)	Team innovation rated by team leaders with West & Anderson's (1999) scale	Did not test any composition models, but reported a positive correlation between average individual innovativeness and team innovation (significant)	No	No
Goncalo & Duguid, (2012)	124 undergraduate student teams participated in the study in exchange for cash reward in United States	Individual creative personality rated by team members themselves with Gough's (1979) scale	Team creativity rated by external coders with an one-item scale	Tested and supported the positive relationship between the proportion of high creative individuals and team creativity	Yes	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Gong et al., (2013)	100 R&D teams from 19 Korean companies across industries of telecommunication, electronics, chemical, aerospace, information technology, and pharmaceutical	Individual creativity rated by team members themselves with Zhou & George's (2001) scale	Team creativity rated by team leaders with Shin & Zhou's (2007)	Tested and supported the relationship between average individual creativity team creativity	Yes	No
Hanke, (2006)	89 student teams from an undergraduate engineering course in United States	Individual creativity rated by peers with Taggar's (2002) scale	Team creativity rated by external raters with 10 items	Did not test any composition models, but reported a negative correlation between average individual creativity and team creativity (insignificant)	No	No
Jin, (2010)	52 research and development (R&D) teams from telecommunication companies in the United States and Korea.	Individual creativity rated by team members themselves with Shalley, Gilson, & Blum's (2009) scale	Team creativity rated by team members with Shin & Zhou's (2007) scale	Did not test any composition models, but reported a positive correlation between average individual creativity and team creativity (insignificant)	No	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Mathisen, Martinsen, & Einarsen, (2008)	29 teams (including production teams, developmental teams, and marketing teams) from a Scandinavian television production company	Individual originality capability rated by team members themselves with Martinsen's (2004) scale	Team innovation rated by external leaders with Scott & Bruce's (1994) scale	Did not test any composition models, but reported a positive relation between average individual originality capability and team innovation (insignificant)	No	No
Miron-spektor et al., (2011)	41 work teams from a large company operating in Israeli defense industry	Proportion of creative individuals rated by team members themselves with Kirton's (1976) scale	Team innovation rated by team leaders with Bonen scale, Darel, Bonen, & Myersdorf's (1993) scale	Tested and supported the positive relationship between proportion of creative individuals and team innovation	Yes	No
Nouri et al., (2013)	96 undergraduate student teams in Singapore	Individual creativity rated by team members themselves with Torrance's (1974) scale	Team creativity coded by external raters with a coding system based on Torrance (1974) and Silvia et al. (2008)	Did not test any composition models, but reported a positive correlation between average individual creativity and team creative performance (significant)	No	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
O’Hara, (2001)	60 MBA student teams from a business course in the United States	Individual creativity rated by external judges	Team creativity rated by external judges with Amabile's (1982) consensual assessment technique	Did not test any composition models, but reported a positive correlation between individual creativity and team creativity (insignificant)	No	No
Pirola-Merlo & Mann, (2004)	56 project teams from four large R&D organizations in Australia	Individual creativity rated by team members themselves with one-item scale	Team creativity rated by team leaders and team members respectively with customized scale on team projects	Did not test any composition models, but reported positive correlation between average individual creativity and team creativity (significant)	No	No
Sacramento et al., (2013)	41 teams from 18 Portuguese organizations involved in a governmental R&D grant	Individual creativity rated by team leaders with customized scale based on work from George & Zhou (2001) and Tierney, Farmer, & Graen (1999)	Team creativity rated by team leaders with customized scale based on work from George & Zhou (2001) and Tierney, Farmer, & Graen (1999)	Did not test any composition models, but reported a positive correlation between average individual creativity and team creativity (significant)	No	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Somech & Drach-Zahavy, (2013)	96 primary care teams from the largest health maintenance organization in Israel	Individual creative personality rated by team members themselves with Gough's (1979) Creative Personality Scale	Team creativity rated by external experts	Tested and supported the positive relation between average creative personality and team creativity	Yes	No
Tadmor et al., (2012)	57 student teams (dyads) from a university for cash reward in United States	Individual creativity coded by external raters	Team creativity coded by external raters	Did not test any composition models, but reported a positive influence of average individual creativity and team creativity	Yes	No
Taggar, (2001)	31 undergraduate student teams from a business course in the United States	Individual creativity rated by peers based on Evan's (1991) scale	Group creativity rated by external judges	Tested and supported the linear (nonlinear) relationship between the number of creative individuals and team creativity, and also reported the influence of highest individual creativity	Yes	Yes

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Taggar, (2002)	94 undergraduate student teams in Canada	Individual creativity rated by peers with a global measure	Team creativity rated by external judges	Did not test any composition models, but reported a positive correlation between average individual creativity and team creativity (significant)	Yes	No
Vera, (2002)	43 teams from municipal departments including Community Services, Works & Transportation, Planning & Building, Legal Services & City Solicitor, Finance, Management Services, and Business Development & Public Relations in Canada	Individual creativity rated by with Tierney, Farmer, & Graen's (1999) scale	Team innovation rated by team members with Roth's (1993) scale	Did not test any composition models	No	No
Wang & Zhu, (2011)	71 work teams from a wide range of organizations in the United States	Individual creativity rated by team leaders with Tierney, Farmer, & Graen's (1999) scale	Team creativity rated by team leaders with Tierney, Farmer, & Graen's (1999) scale	Did not test any composition models, but reported a positive correlation between average individual creativity and team creativity (insignificant)	No	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
West & Anderson, (1996)	27 top management teams from major hospitals in UK	Proportion of innovative individuals rated by team members themselves with Burningham & West's (1995)	Team innovation reported by team members with West's (1987) scale	Tested and supported the positive relationship between the proportion of innovative individuals and team innovation	Yes	No
Yoshida, Sendjaya, Hirst, & Cooper, (2014)	154 work teams from Indonesian and Chinese firms in various industries (e.g., finance, heavy manufacturing and telecommunications).	Individual creativity rated by team leaders with Baer and Oldham's (2006) scale	Team innovation rated by team leaders with De Dreu's (2006) scale	Did not test any composition models, but reported a positive correlation between average individual creativity and team innovation (significant)	No	No
Navaresse, Yauch, Goff, & Fonseca, (2014)	36 student teams of engineering undergraduates and graduates in the United States	Individual creativity rated by peers with a scale mixing Taggar's (2002) measure and Amabile's (1996) measure	Team creativity rated by external judges	Tested and supported a positive relationship between average individual creativity and team creativity	Yes	No

Studies	Samples	Individual creativity	Team creativity	Findings	Additive model	Disjunctive model
Kurtzberg, (2000)	Sample 1: 26 teams from 7 different organizations in three different industries (chemical/pharmaceutical, high-tech, and consumer products)	Individual creative style rated by team members themselves with Kirton Adaptation-Innovation (KAI) inventory	Team creativity rated by team members and external managers respectively	Tested and supported (marginally) the positive relationship between individual creative styles and team creativity	Yes	No
	Sample 2: 76 student teams in a business school course of negotiations in United States	Individual creative style rated by team members themselves with Kirton Adaptation-Innovation (KAI) inventory	Team creativity rated by external raters	Tested and found no support for the positive relationship between individual creative styles and team creativity, but reported a positive correlation (insignificant)	Yes	No

Chapter 4 Leader Centrality and Team Performance in Directed Advice Networks: Two Mediated Moderation Models

Introduction

The development of social network theories has greatly advanced our understanding of team leadership (Carson, Tesluk, & Marrone, 2007; Day, Gronn, & Salas, 2006; Mehra, Dixon, Brass, & Robertson, 2006). Scholars have widely acknowledged that leadership functions are carried out and embedded within team networks (Carson et al., 2007; Kilduff & Balkundi, 2011; Kilduff, Tsai, & Hanke, 2006; Mehra, Smith, Dixon, & Robertson, 2006; Zohar & Tenne-Gazit, 2008). Nevertheless, given the complexity of interpersonal dynamics and leadership processes in today's work teams (Cummings & Cross, 2003; Jehn, Rispens, & Thatcher, 2010), the embedded leadership functions in team networks do not necessarily lead to effective leadership outcomes (e.g., Mehra, Dixon, et al., 2006). More central to understanding the embedded function of team leadership, research has begun to explore how team leaders interpret and make use of their network resources in leadership processes (Balkundi & Kilduff, 2006; Balkundi, Kilduff, & Harrison, 2011; Carter, DeChurch, Braun, & Contractor, 2015; Sparrowe & Liden, 2005).

To understand such network resources of team leaders, the most intuitively important notion is known as network centrality, which captures the number of interpersonal connections one has to the others in a given network (Bonacich, 1987; Borgatti & Everett, 2006). Social network theories assume that interpersonal connections are network resources. The more connections an individual possesses in a network, the more central his/her position is. Depending on the nature of interpersonal networks, high centrality may reflect various types of network resources, ranging from preference (e.g., in a network of who likes whom) or hatred (e.g., in a network of who dislikes whom), or from influence (e.g., in a network of helping team members) to vulnerability (e.g., in a network of receiving help from team members). In the domain of team leadership research, a number of studies have examined the relationship between a leader's network centrality and team performance, and found inconsistent results (Balkundi & Kilduff, 2006; Balkundi et al., 2011; Kratzer, Leenders, & van Engelen, 2008; Mehra, Dixon, et al., 2006). Balkundi and Harrison (2006) concluded this argument with a meta-analysis of 13 studies, showing that leader's network centrality is positively related to team performance. Team leaders with a high level of network centrality have abundant network resources for team leaders to promulgate team objectives, to motivate team members and to coordinate team activities in order to achieve team successes.

Nevertheless, as pointed out by social network theories, the amount and value of such network resources are often subject to the structural characteristics of team networks such as network nature and network size (Borgatti et al., 2013; Krackhardt, 1990). For instance, although the central position in a network of helping (i.e., providing help to) team members implies influence and power, the central position in a network of receving help from team members signals more of dependence and vulnerability (Agneessens & Wittek, 2012). Also, the central position in a team network of 3 members is less valuable for team leadership than that in a team network of 20 members. Explorations of such contextual conditions, however, were absent in prior empirical studies, including Balkundi and Harrison's (2006) meta-analytic review. More importantly, the argument that leader centrality influences team performance by coordinating team members' work processes has never been tested (Balkundi et al., 2011). This, therefore, leaves our understanding of the relationship between leader's network centrality and team performance imprecise. In response to recent calls for more nuanced investigation of team leadership functions (Day et al., 2006; Dinh et al., 2014), we therefore investigate when and how a leader's network centrality shapes team performance.

As team size directly speaks to the magnitude of network resources that team leaders may gain from central positions and thus to the value of leadership interventions (Amason & Sapienza, 1997; Poulton & West, 1999), we scrutinize the moderating role of team size on the relationship between leader centrality and team performance in both the advice-giving network and the advice-receiving network. We chose to observe the directed advice networks for two reasons: first, advice networks have been widely used to understand task-oriented communication at workplaces (e.g., Sparrowe, Liden, Wayne, & Kraimer, 2001). Secondly, sending and receiving advice denote entirely different network resources and liabilities (Borgatti et al., 2013; Ibarra, 1992). We first propose that the relationship between leader centrality in the advice-giving network and team performance is more positive when team size is large as opposed to small. Large teams with more complicated communication patterns often have stronger needs for leadership coordination and also more network resources for holders of central positions. Leaders with high network centrality, therefore, have more influence and can also provide more value to guide subordinates via providing work-related suggestions than in small teams. For advice-receiving networks, however, where centrality equates vulnerability, we propose that the relationship between leader centrality and team performance is less positive when team size is large as opposed to small. This is because central leaders receiving most advice from subordinates tend to be less available and credible to fulfill their leadership duties in large teams that have stronger needs for leaders' interventions (Kratzer et al., 2008).

We examine two independent mediators to account for moderated effect of leader centrality in the advice-giving network and the advice-receiving network, based on the notion that the network resources embedded in central positions will only come into play when the recipients of such resources recognize and deploy them in task-relevant processes (Shannon & Weaver, 1949). In this sense, to what extent leader centrality plays its role in the advice-giving and advice-receiving networks really depends on the extent to which subordinates (i.e., the recipients of central leaders' advice) and central leaders (i.e., the recipients of followers' advice) respond to such network resources and employ them. Therefore, we propose that subordinate collaboration—the collective activities among subordinates to translate disposable resources into team solutions—mediates the interaction between leader centrality in the advice-giving network and team size in determining team performance. Because subordinate collaboration captures the extent to which team members effectively coordinate and apply the varying network influences (i.e., downward suggestions) of central leaders in team processes in order to promote team performance. We also propose that a leader's sense of power—his/her subjective motives to act upon social influences (Anderson & Berdahl, 2002; Anderson, John, & Keltner, 2012)—mediates the interaction between leader centrality in the advice-receiving network and team size in determining team performance. The rationale is that: centralized upward advice to the central leaders creates team leaders' dependence upon subordinates and lowers their perceived power (Agneessens & Wittek, 2012; Mehra, Smith, et al., 2006), and therefore prohibits central leaders from expressing their opinions, circulating team objectives and coordinating team dynamics that will promote team performance (Anderson & Berdahl, 2002; Galinsky, Gruenfeld, & Magee, 2003).

In response to Carter and colleagues' (2015) call for empirical attentions to the boundary conditions and influential mechanisms of how team leadership in networks functions, the present study aims to elucidate when and how leader centrality influences team performance in directed advice networks. Extending Balkundi and Harrison's (2006) meta-analytic result of the relationship between leader centrality and team performance, we present the contextual impact of team size in specific networks. This broadens our understanding of when leader centrality benefits or even hinders team performance. More central to understanding the function of leader's network resources in team activities, we provide insights into the influential mechanism of leader's network resources by testing two independent influential paths in the advice-giving and advice-receiving networks.

Theory and Hypotheses

Leader Centrality in Directed Advice Networks and Team Performance

From a network perspective, team leadership is a relation phenomenon that is situated in social interactions (Carter et al., 2015). The effectiveness of team leadership is subject to not only team complexities and needs (Day et al., 2006; Yukl, 2002), but also to the network positions that leaders occupy. Because different network positions vary in the amount and intensity of connectivity, which is a network resource that determine the impacts of place holders (Bonacich, 1987; Borgatti & Everett, 2006). Team leaders, being embedded in team networks, ought to set compelling directions for teams, to enable coordinated, integrated, and adaptive team processes that accomplish team tasks. Network centers—often operationalized via the centrality index—have obtained most attention in team and leadership research, as central positions allow team leaders to concentrate resources such as expertise, trust, and emotions, while diffusing their influences to subordinates (Kilduff & Krackhardt, 2008; Raider & Krackhardt, 2002). Among all kinds of team networks, advice networks capture network resources that are most relevant to team activities and objectives, as they directly denote how team members exchange problem-solving inputs in order to achieve team success (Agneessens & Wittek, 2012; Sparrowe et al., 2001). More importantly, the increasing attention to the directions of network ties in social network research evokes empirical concerns about the distinction between advice-giving and advice-receiving networks, as providing advice grants influence and power whereas receiving advice imposes obligations and dependence (Soltis, Agneessens, Sasovova, & Labianca, 2013; Zagenczyk & Murrell, 2009).

A number of studies explored the link between leader centrality and team performance. In some studies, a positive link was identified between leader centrality in advice networks and team performance, such that central leaders could gather dispersed individual resources and better monitor and optimize team activities and processes (e.g., Balkundi, Barsness, & Michael, 2009; Balkundi et al., 2011; Friedkin & Slater, 1994). Yet in some other studies, scholars evidenced a negative relationship, arguing that central leaders are prone to experience information overload and thus unable to coordinate team resources properly (e.g., Kratzer et al., 2008). Despite such contradictory findings, Balkundi and Harrison (2006) presented a meta-analytic evidence that team performance was positively related to leader centrality in advice networks as well as in other team networks, such as friendship and affect networks. As the only meta-analytic review in this stream of research, Balkundi and Harrison's (2006) work reinforced the significance of leader centrality in understanding team leadership from a network perspective and invited more empirical attention to explore when and how such impacts occur. After all, the existence of an overall positive effect does not exclude the possibility of contextual moderators.

As pointed out in social network literature, the network resources captured in the notion of leader centrality do not affect teams in isolation (Kilduff & Tsai, 2003). Many other network features, particularly the structural characteristics of team networks such as network nature and network size, together determine the value of leader centrality under specific circumstances. For instance, leader centrality in advice-giving networks exerts a totally different impact on team functioning than in advice-receiving networks (Ibarra, 1992; McElroy, 1986). In an advice-giving network, a central position indicates maximum resources to direct others' opinions and behaviors, yet in an advice-receiving network, it implies network resources to receive help and to be influenced. Therefore, it is important to distinguish the two types of advice connections. On the other hand, network size specifies the magnitude of network resources that central positions may bring to team leaders. Central leaders have a wider influence in a large network than in a small one. Large teams also have more cognitive resources to balance receiving advice from central leaders and developing their autonomous problem-solving approaches. Whereas in small teams spontaneous information flows among team members are more likely to be distracted or suppressed by information flows from the central leaders (Brass & Burkhardt, 1993; Leenders et al., 2003).

The Moderating Role of Team Size in Directed Advice Networks

Team size is a parsimonious yet rather significant determinant of team requirements (Amason & Sapienza, 1997). As team size grows, team processes get more complex and demanding (Jackson, 1996). Cognitive resources at one's disposal, such as diverse expertise, social capitals, and various views, increase as team size increases, yet also cast great challenges on interpersonal communication, regulation, and collaboration within work teams (Guzzo & Shea, 1992). Large teams suffer more from process losses than small teams due to the complexity of team collaboration and synergy (Latané, Williams, &

Harkins, 1979; Peltokorpi & Hasu, 2014). For example, in comparison to small teams, large teams might be less motivated to participate in team information processes (Peltokorpi & Hasu, 2014), have more cognitive and affective conflicts (Amason & Sapienza, 1997), are less involved in team decision-making (Curral et al., 2001), and more prone to split into subgroups (Carton & Cummings, 2012).

Hence, complex communication patterns and substantial coordination obstacles in large teams call for external regulations to optimize team processes. Central hubs of advice-giving networks enable team leaders to disseminate their influence to subordinates, allowing them to clarify team objectives, facilitate interpersonal communications, and provide advice on technical or interpersonal issues. This is consistent with the positive argument that leader centrality improves team performance (Balkundi & Harrison, 2006). Yet in small teams, where communication patterns are rather straightforward and self-organized, central intervention from team leaders is less needed than full engagement of subordinates in collective problem-solving activities. Moreover, communicating with central leaders consumes employees' cognitive resources and competes with other task-related communication among team members. Such competition of cognitive resources is more salient in small teams, where the cognitive resource is less abundant than in large teams. Small teams are more likely to suffer from centralized communication around team leaders. As a result, leader centrality in the advice-giving network may sidetrack subordinators from developing their own problem-solving processes for team successes in small teams. Thus, we propose:

Hypothesis 1: Team size moderates the relation between leader centrality in the advice-giving network and team performance, such that leader *centrality is more positively related to team performance in large teams than in small teams.*

Central positions in advice-receiving networks, in contrast, lead to team leaders absorbing most attention and work-related suggestions from the subordinates. As suggested in the prior literature (e.g., Balkundi & Harrison, 2006), the sizeable advice flows from subordinates to the network center allow team leaders of high network centrality in the advice-receiving networks to gain an accurate picture of team dynamics, which potentially benefits central leaders' judgments and more effective regulations on team processes. Nevertheless, such abundant advice flows may also risk overloading the central leaders, particularly in large teams that contain a great number of advice flows. As extending and utilizing information ties requires cognitive investments, receiving and absorbing incoming knowledge flows tends to burden central leaders, who may then have insufficient time and resources to deploy such resources in their strategic intervention on teams (Kratzer et al., 2008). Given that large teams have stronger needs for external intervention from team leaders, such a risk of advice oversupply is more pressing for central leaders in large teams than in small teams. Therefore, the risks of insufficient cognitive resources and the urgent needs for leadership coordination from team leaders in advice-receiving networks in large teams makes leader centrality less advantageous in large teams than in small teams. Thus, we predict:

Hypothesis 2: Team size moderates the relation between leader centrality in the advice-receiving network and team performance, such that leader centrality is less positively related to team performance in large teams than in small teams.

Subordinate Collaboration as a Mediator in the Advice-Giving Network

Arguments about how leader centrality shapes team performance rely on two assumptions: first, team leaders in central positions shape team performance through facilitating and/or hindering collective processes among team members (Kratzer et al., 2008; Mehra, Dixon, et al., 2006); and second, when receiving network advantages in the central positions, team leaders do make use of such network resources in teams by providing information, establishing rapport or confidence, and inspiring subordinates to engage in work tasks (Balkundi et al., 2011), as opposed to holding such resources to themselves. The recipients of advice inputs—either the subordinates in the advice-giving network or the central leaders in the advice-receiving network—must transmit the network inputs of information and influence into team dynamics. In other words, when giving advice to employees in the intra-team network, central leaders need to make sure such inputs are reflected in subordinate processes that are relevant to team tasks. When receiving work-related advice from followers, central leaders have to employ such resources in their leadership actions towards team members. Nevertheless, prior literature rarely investigated the influential mechanisms of leader centrality (e.g., Balkundi et al., 2011), let alone specified distinctive pathways in directed team networks. Particularly, as the size of work teams directly determines the intensity of both the needs for and availability of leadership interventions from the network centers, it is, therefore, valuable to explore how the moderating impact of team size on the relationship between leader centrality in directed advice networks and team performance occur.

We propose that subordinate collaboration mediates the interaction between leader centrality in the advice-giving network and team size on team performance. Subordinate collaboration refers to the collective work of converting disposable resources into team solutions (LePine, Piccolo, Jackson, Mathieu, & Saul, 2008; Reagans & Zuckerman, 2001;

Zaccaro, Rittman, & Marks, 2001). A high level of subordinate collaboration facilitates the utilization of received suggestions and feedback on work-related matters and thus promotes team performance (LePine et al., 2008; Reagans & Zuckerman, 2001; Zaccaro et al., 2001). By extending advice to team members, team leaders with high centrality in the advice-giving network determine what and how team members engage in problem-solving activities. Thus, the influence of leader centrality relies on the extent to which team members absorb and utilize leaders' advice in their problem-solving activities. More importantly, both social network theories and empirical findings point to the contingent effect of high network centrality, such that central network positions bear both information advantages and potential risks of hindering the communication among other members (Borgatti et al., 2013).

In large teams, there is often a strong need for central leaders to coordinate the complex interpersonal dynamics among a large number of team members. In the meantime, ample cognitive and personnel resources enable large teams to organize their interpersonal dynamics besides direct contacts with their central leaders. Therefore, leaders with a high level of centrality in the advice-giving networks of large teams tend to facilitate subordinate coordination, which results in a higher level of team performance. In small teams, however, the need for leadership coordination is less salient, whereas the risk of central leaders distracting team members from forming their own problem-solving approaches with firsthand suggestions is more notable. As suggested in prior network studies, the more suggestions team members receive from the central leaders, the less likely they will seek work-related advice elsewhere (Kratzer et al., 2008). When team leaders possess the central positions of advice-giving networks, subordinates might depend more on their central leaders than on their peers for suggestions in problem-solving (Balkundi et al., 2009). This will result in a lower level of subordinate collaboration among team members and further lower the team performance. Thus, we expect:

Hypothesis 3: Leader centrality in the advice-giving network and team size jointly impact team performance via the mediating role of subordinate collaboration.

Leader's Sense of Power as a Mediator in the Advice-Receiving Network

Whereas the crucial role of translating the impact of leader centrality in the advice-giving network is to have the recipients of advice ties—team members—incorporate leaders' inputs in collective collaboration, the key to realize the network impacts of team leaders in the advice-receiving networks also lies in the recipients of advice ties—to what extent team leaders fulfill their expectations to intervene and influence. To explain the joint impact of leader centrality in the advice-receiving network and team size on team performance, we propose a mediating role of team leader's sense of power—a psychological state that determines leader's motivation to interfere and improve team activities (C. Anderson & Berdahl, 2002; C. Anderson et al., 2012). The notion of leader's sense of power differs from the designated power in leadership roles. The former is about a leader's subjective perception of one's capacity to influence (C. Anderson et al., 2012; Keltner, Gruenfeld, & Anderson, 2003); whereas the latter refers to the control over resources coming from the leadership positions (Hogg, 2001). The inherent power in leadership positions does not necessarily incite leader's motivation to interfere and impact the social processes in teams. For instance, Galinsky and colleagues (2003) found that individual sense of power directly triggers goal-directed behaviors and performance, whereas designated power only leads to interventions when it evokes a high sense of power in the power holders. In the context of advice-receiving networks, the key to translating the joint effect of leader centrality and team size into team performance lies in leaders' sense of power—to what extent leaders feel motivated to optimize collective activities and processes.

The sense of power is a relational product (Keltner et al., 2003). To what extent one develops a sense of power is largely determined by his/her social experiences that shape subjective beliefs, expectations, and affections about influencing the others. From the perspective of social networks, information connections create dependence and sense of power (Ibarra & Andrews, 1993). Individuals who provide suggestions obtain information power over others. Those who receive information tend to rely on the others and experience less power. In small teams, where central leaders receive a large number of advice ties from the subordinates, central leaders in advice-receiving networks tend to experience a low level of power. According to the approach/inhabitation theory of power, experiencing a low level of power increases the tendency to inhibit and decreases the tendency to approach (C. Anderson & Berdahl, 2002; Keltner et al., 2003). More specifically, individuals feeling a low sense of power tend to speak less (Dovidio, Brown, Heltman, & Ellyson, 1988), keep their opinions to themselves (Asch, 1955; Milgram, 1963), and exert less social inputs on others' behaviors, opinions, and decisions (C. Anderson & Berdahl, 2002). Likewise, central leaders in large teams also suffer from a low level of sense of power, which lowers the effectiveness of leadership interventions. Moreover, central leaders in large teams are more likely to experience information overload and therefore have less time and fewer motives for intervention activities than those in small teams, which will then result in lower level of team performance. Therefore, we propose:

Hypothesis 4: Leader centrality in the advice-receiving network and team size jointly impact team performance via the mediating role of leader's sense of power.

Method

Data and Sample

Data were collected from seventy-five franchised stores of a bakery group located in the central part of China[5]. All these seventy-five franchises stores share the same settings: Each franchised store operates independently and takes full responsibility for its performance as a collective. Each store manager or team leader actively monitors its progress and achievement, and together with employees adjusts its strategies to performance requirements and customer feedback. Such setup qualifies for our intention to observe the impact of leader centrality on team performance.

To avoid the common method bias, we sent out paper-and-pencil questionnaires to employees and team leaders (i.e., store managers) respectively in two weeks. In the first week, five research assistants administered the surveys to team members on-site and collected them back right away to ensure the confidentiality of their responses. One week later, questionnaires were distributed to all team leaders at a monthly review meeting in the headquarter office. Reminders were sent to absent employees and leaders in the following week. In total, 567 out of 577 employees filled out the subordinate questionnaires, and 73 out of 75 team leaders filled out the supervisors' counterparts. After matching two parts up, we included 552 employees and 72 team leaders from 72 teams ranged from 4 to 22 members (M_{size} = 8.67, SD_{size} = 3.27).

Measures

Leader centrality. We measured leader centrality with a widely adopted roster method (Perry-Smith, 2006). All employees rated the frequency of their advice-giving and

[5] This chapter uses the same data set as the first empirical chapter, but different variables.

advice receiving activities respectively toward both their coworkers and team leaders, on a 6-point Likert scale (1= "less often", 2 = "several times a year", 3 = "once a month", 4 = "several times a month", 5 = "several times a week", 6 = "daily"). Questions on the advice-giving and advice-receiving networks are: "*To what degree do you give professional advice to this person when he/she has a work-related problem*?" and "*To what degree do you receive professional advice from this person when he/she has a work-related problem*?". We calculated Bonacich's power centrality (beta centrality) of each team leader in directed advice networks in UCINET (Borgatti, Everett, & Freeman, 2002). This measure is often used in leadership literature (e.g., Mehra, Dixon, Brass, & Robertson, 2006), as it captures the actual influence of leader by taking the influences of connected individuals into account (Bonacich, 1987).

Team performance. To guarantee the ecological validity of the performance measure, we developed a performance scale based on the performance criterion in this company after interviewing the Chief Operation Officer and the Human Resource Director in headquarter. Team performance was rated by team leaders with a four-item scale on the following dimensions: (1) the overall quality of teamwork, (2) the work efficiency as a team, (3) the punctuality of teamwork, and (4) performance requirements on each sales season. Standardized Cronbach's alpha of this measure is 0.71.

Team collaboration among subordinates. Team leaders rated team collaboration among subordinates, using a one-item scale from 1 to 10. The item is: "*Team members collaborate with each other and achieve team tasks together*".

Leader's sense of power. Team leaders rated their subjective sense of power with a 7-item scale adapted from Anderson, John, & Keltner's (2012) inventory of personal sense of power, on a 10-point basis. Instruction lines were provided to specify the context of team interactions. Standardized Cronbach's alpha of this measure is 0.60. Sample items are "*I can get my subordinates to do what I want*", and "*I can get my subordinates to listen to what I say*".

Control variables. We controlled three factors that might influence the relationship between leader centrality and team performance. First, we controlled average individual performance to underline the distinctive impact of leader centrality on team outcomes. This is because, according to the multilevel system of team phenomena from Klein & Kozlowski (2000) and Kozlowski & Klein (2000), gathering high performers in teams naturally increases team performance. Team leaders rated the individual performance of each subordinate on four aspects: (1) job obligations and requirements, (2) punctuality on work tasks, (3) work quality, and (4) conformity to norms and regulations. Standardized Cronbach's alpha of this measure is 0.82. Secondly, we controlled average conscientiousness among team members, as this personality trait was found to be positively associated with high team performance in Peeters, Van Tuijl, Rutte, and Reymen's (2006) meta-analytic review as well as in other empirical tests (van Vianen & De Dreu, 2001). Lastly, average team tenure of individual members was controlled to minimize the influence of familiarity on employees' advice-giving and advice-receiving behaviors, as team tenure affects how individuals participate in social networks activities (Mehra, Kilduff, & Brass, 2001; Reagans & Zuckerman, 2001).

Discriminant validity. Given that team leaders reported both team collaboration and team performance, we conducted Confirmatory Factor Analysis to test the discriminant validity of these two measures. Researchers have recommended several criteria for fitting models, such as TFI and CFI scores of at least 0.95, SRMSR values lower than 0.08, and RMSEA values lower than 0.10 (Kenny, Kaniskan, & McCoach, 2014; Vandenberg &

Lance, 2000). In our sample, a two-factor model was found supporting the measurement variance between two variables (TLI = .92, CFI = .96, SRMSR = .06, and RMSEA = .10).

Analysis and Results

Means, standard deviations, and correlations of the variables are presented in Table 6.

Table 6. Means, Standard Deviations, and Correlations [a]

Variables	Mean	S.D.	1	2	3	4	5	6	7	8
1. Team performance	7.65	1.16	-							
2. Leader centrality in advice-giving network	0.98	0.20	-.08	-						
3. Leader centrality in advice-receiving network	1.14	0.18	-.15	.66**	-					
4. Team size	8.67	3.27	.03	-.06	.24*	-				
5. Team collaboration among subordinates	8.75	1.45	.64***	-.12	-.19	-.12	-			
6. Leader's sense of power	7.69	1.02	.41***	-.01	-.19	-.11	.36**	-		
7. Average individual performance	7.33	0.98	.40***	.06	.11	.02	.31**	.19	-	
8. Average team member conscientiousness	7.23	0.57	.12	-.02	-.04	-.19	.20†	.14	.14	-
9. Average team tenure [b]	1.10	0.38	.12	-.17	-.18	-.14	.09	-.06	.06	-.15

a N = 72. b N = 71.

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$.

We first tested our Hypotheses 1 and 2 in hierarchical regression models. As predicted in Hypothesis 1, we found a positive interplay between leader centrality in the advice-giving network and team size in shaping team performance (ΔR^2 = .10, *b* = .15, *t* = 2.95, *p* < .01, 95% BCa CI = [0.05, 0.25]), with the overall moderation model contributing to 29% of the variance of team performance (see Table 7). Results also revealed a significant interaction between leader centrality in the advice-receiving network and team size on team performance (*b* = -.10, *t* = -1.71, *p* < .1, 95% BCa CI = [-.23, -.02]), supporting Hypothesis 2 (see Table 7). This moderation model explained 25% of the variance of team performance, with the interaction term alone explaining 3% of the variance of team performance. Both moderation effects are plotted in Figure 4 & 5.

Table 7. Regression Results of Hypotheses [a]

Variables	R^2	*b*	*t*	95% CIs	
				Lower	Upper
Hypothesis 1					
Constant		7.43	20.60***	6.71	8.15
Average performance in team		0.40	3.20**	0.15	0.66
Average team tenure		0.12	0.96	-0.13	0.38
Average conscientiousness		0.07	0.54	-0.19	0.33
Leader centrality in advice-giving network		-1.30	-3.05**	-2.15	-0.45
Team size		0.03	0.72	-0.05	0.11
Leader centrality × team size		0.15	2.95**	0.05	0.25
ΔR^2	.10**				
R^2	.29**				
Hypothesis 2					
Constant		7.01	16.58***	6.16	7.85
Average performance in team		0.45	3.51***	0.19	0.71
Average team tenure		0.13	0.96	-0.14	0.39
Average conscientiousness		0.16	1.19	-0.11	0.43
Leader centrality in advice-receiving network		0.63	1.21	-0.41	1.68
Team size		0.08	1.67†	-0.02	0.18
Leader centrality × team size		-0.10	-1.71†	-0.23	-0.02
ΔR^2	.03†				
R^2	.25**				

a. *N* = 71.
*** *p* < .001. ** *p* < .01. † *p* < .1.

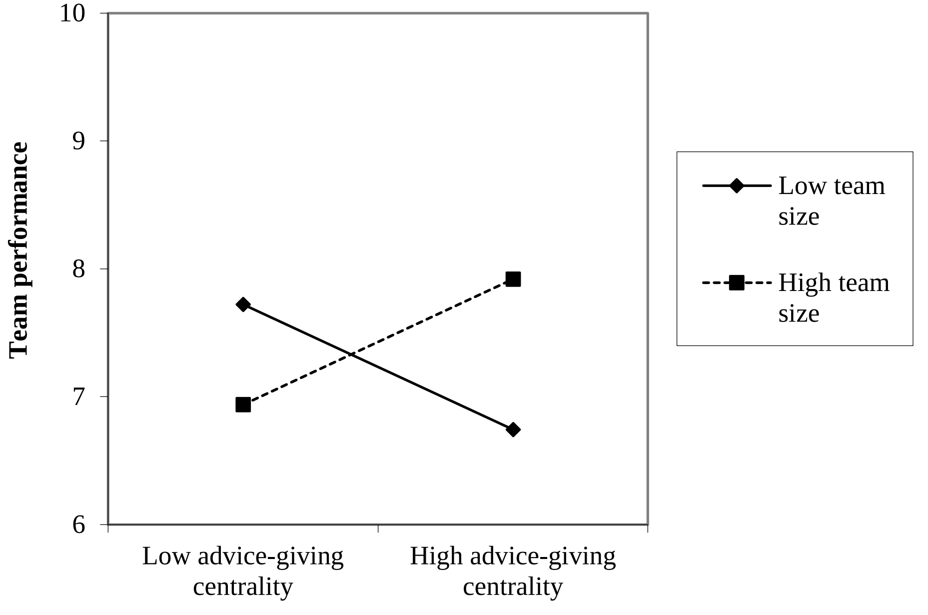

Figure 4. Interaction Effect of Leader's Advice-giving Centrality and Team Size on Team Performance

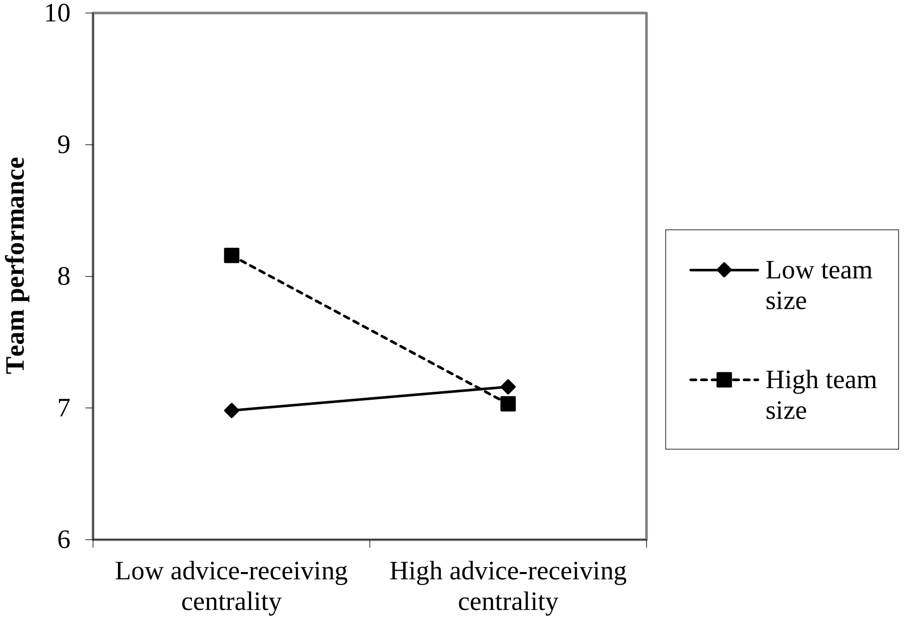

Figure 5. Interaction Effect of Leader's Advice-receiving Centrality and Team Size on Team Performance

Table 8. Conditional effect of leader centrality in the advice-giving network on team performance across values of team size

Team size	Effect	*SE*	*t*	95% Confidence Interval	
				Lower	Lower
4	-0.71	0.24	-2.92^{***}	-1.19	-0.22
5	-0.56	0.20	-2.78^{**}	-0.96	-0.16
6	-0.41	0.17	-2.50^{*}	-0.74	-0.08
7	-0.27	0.14	$-1.92^{\dagger}$	-0.54	0.01
8	-0.12	0.13	-0.94	-0.37	0.13
9	0.03	0.13	0.22	-0.24	0.30
10	0.18	0.16	1.13	-0.14	0.49
11	0.32	0.19	$1.71^{\dagger}$	-0.06	0.70
12	0.47	0.23	2.05^{*}	0.01	0.93
13	0.62	0.27	2.27^{*}	0.07	1.17
14	0.77	0.32	2.41^{*}	0.13	1.40
15	0.91	0.36	2.51^{**}	0.19	1.64
16	1.06	0.41	2.58^{**}	0.24	1.89
17	1.21	0.46	2.63^{**}	0.29	2.13
18	1.36	0.51	2.67^{**}	0.34	2.37
19	1.50	0.56	2.70^{**}	0.39	2.62
20	1.68	0.62	2.73^{**}	0.45	2.91
21	1.81	0.66	2.75^{**}	0.50	3.13
22	1.95	0.70	2.77^{**}	0.54	3.35

† $p < .1$, * $p < .05$, ** $p < .01$.

In order to elucidate the interplay between leader centrality and team size in directed advice networks (Hypothesis 1 & 2) , we probed the significant regions of two main effects with Johnson & Neyman's (1936) technique to depict the varying impact of leader centrality on team performance across different values of team size (Preacher, Curran, & Bauer, 2006). Tan's (2015) R package '*probemod*' was used for this analysis. As shown in Table 3, leader centrality in the advice-giving network is negatively associated with team performance when teams possess less than 8 members. As team size increases, the influence of leader centrality in the advice-giving network turns insignificant in teams of 8 to 11 members and then becomes positive in large teams of more than 11 members (see Table 8). In a similar fashion, leader centrality in the advice-receiving network exerts no influence on team performance of small teams of less than 9 members, but a negative influence on that of medium to large teams of more than 9 members (see Table 9).

Table 9. Conditional effect of leader centrality in advice-receiving network on team performance at values of team size

Team size	Effect	*SE*	*t*	95% confidence interval	
				Lower	Lower
4	0.22	0.29	0.74	-0.37	0.80
5	0.11	0.24	0.47	-0.37	0.59
6	0.01	0.19	0.04	-0.38	0.39
7	-0.10	0.15	-0.62	-0.40	0.21
8	-0.20	0.13	-1.50	-0.47	0.07
9	-0.30	0.14	-2.19^{*}	-0.58	-0.03
10	-0.41	0.17	-2.42^{*}	-0.75	-0.07
11	-0.51	0.21	-2.42^{*}	-0.94	-0.09
12	-0.62	0.26	-2.35^{*}	-1.14	-0.09
13	-0.72	0.32	-2.27^{*}	-1.35	-0.09
14	-0.83	0.37	-2.21^{*}	-1.57	-0.08
15	-0.93	0.43	-2.16^{*}	-1.79	-0.07
16	-1.03	0.49	-2.11^{*}	-2.01	-0.05
17	-1.14	0.55	-2.07^{*}	-2.23	-0.04
18	-1.24	0.61	-2.04^{*}	-2.46	-0.03
19	-1.35	0.67	-2.01^{*}	-2.68	-0.01
20	-1.47	0.74	$-1.99^{\dagger}$	-2.95	0.01
21	-1.56	0.79	$-1.97^{\dagger}$	-3.15	0.02
22	-1.66	0.85	$-1.95^{\dagger}$	-3.35	0.04

† $p < .1$, * $p < .05$, ** $p < .01$.

We tested two mediated moderation models in the advice-giving (Hypothesis 3) and advice-receiving networks (Hypothesis 4) with the R package "*mediation*" for causal mediation relations (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). This method enables us to identify the exact indirect effects at specific values of the moderator—team size—and thus provides a more accurate picture of the mediated moderation effect. Following Mackinnon, Lockwood, & Williams's (2004) advise on causal mediation effect testing, we used bias-corrected bootstrapping simulation method to construct confidence intervals for indirect effects[6]. Our Hypothesis 3 predicts that subordinate collaboration mediates the moderating role of team size on the relationship between leader centrality in the advice-giving network and team performance. More specifically, we anticipate that leader centrality in the advice-giving network demotivates subordinates from collaborating together and therefore impairs team performance of small teams, but facilitate subordinates to collaborate with each other and in turn improves team performance of large teams. We thus tested whether team collaboration mediates the relationship between leader centrality and team performance in those small teams of less than 8 members—as identified in Johnson & Neyman's (1936) region of significance analysis (see Table 8). As shown in table 10, the indirect effect of leader centrality on team performance via team collaboration is significant across these small teams, with an average causal mediated effect (ACME) of -0.12 (95% BCa CI = [-0.28, -0.02], $p < .05$). We also tested whether team collaboration mediates the negative relation between leader centrality and team performance in those large teams of more than 11 members—as identified in Johnson & Neyman's (1936) region of significance analysis (see Table 8). Inconsistent with our expectation, our results did not support the indirect effects of leader centrality on team performance via team collaboration in large teams, with an average causal mediated effect (ACME) of 0.51 (95% BCa CI = [-0.44, 2.19], $p > .1$). Thus, Hypothesis 3 is partially supported.

Likewise, to examine Hypothesis 4, we tested the indirect effects in small teams of less than 8 members and large teams of more than 9 members respectively—identified in aforementioned Johnson & Neyman's (1936) region of significance analysis (see Table 9). As shown in Table 10, the indirect effect of leader centrality in the advice-receiving network

[6] We also followed Preacher & Selig's (2012) advise to deploy Monte Carlo simulation for a comparison. Results of two simulation approaches were consistent.

on team performance through leader's sense of power is significant across these small teams, with an average causal mediated effect (ACME) of -0.06 (95% BCa CI = [-0.28, -0.01], $p < .05$). The mediating role of leader's sense of power between the relationship of leader centrality and team performance was also supported in large teams, with an average causal mediated effect (ACME) of -3.32 (95% BCa CI = [-6.55, -0.17], $p < .05$).

Table 10. Conditional Negative Effects of Leader Centrality on Team Performance across Values of Team Size

Level of team size	Indirect effect		Direct effect		Total effect		Proportion mediated	
	Estimate (SE) [a]	95% CI	Estimate (SE) [a]	95% CI	Estimate (SE) [a]	95% CI	Estimate (SE) [a]	95% CI
Advice-giving network (Hypothesis 3)								
Mean (4:7)	-0.12^{*}	[-0.28, -0.02]	-0.13	[-0.30, 0.19]	-0.26^{*}	[-0.44, 0.11]	$0.47^{\dagger}$	[-0.14, 4.67]
Mean (122)	-0.51	[-0.44, 2.19]	$1.41^{\dagger}$	[-0.17, 2.67]	$1.92^{\dagger}$	[-0.41, 3.31]	0.27	[-2.51, 0.88]
Advice-receiving network (Hypothesis 4)								
Mean (4:8)	-0.06^{*}	[-0.28, -0.01]	0.13	[-0.28, 0.19]	$-0.20^{\dagger}$	[-0.47, 0.03]	0.33^{*}	[0.10, 29.04]
Mean (9:22)	-3.32^{*}	[-6.55, -0.17]	0.33	[-1.34, 2.06]	-2.99	[-6.04, 0.58]	$1.11^{\dagger}$	[1.37, 157.70]

† $p < .1$, * $p < .05$.
N = 71.
Note. CI = confidence intervals.
a Estimates for standard error (SE) were bootstrapped for 10000 times.

Discussion

Aiming to provide a fine-grained picture of when and how leader centrality shapes team performance in directed advice networks, we tested the moderating role of team size and two mediated moderation models via subordinate collaboration in advice-giving networks and leader's sense of power in advice-receiving networks respectively. As shown in our results, the relationship between leader centrality and team performance is more positive in advice-giving networks of large teams (Hypothesis 1) but less positive in advice-receiving networks of large teams (Hypothesis 2). More specifically, leader centrality in the advice-giving network promotes team performance in large teams of more than 12 members but impairs team performance in small teams of less than 8 members. In the advice-receiving network, however, leader centrality hinders team performance in teams of more than 9 members but has no significant impact on team performance in small teams of less than 9 members. We further found two independent influential mechanisms of such moderated effects of leader centrality in directed advice networks. Subordinate collaboration partially mediated the moderated effect of leader centrality in advice-giving networks (Hypothesis 3), as it mediated such joint impacts only in small teams, but not in large teams. On the other hand, leader's sense of power mediated the moderated effect of leader centrality in advice-receiving networks (Hypothesis 4).

Theoretical Implications

In unpacking these findings, we contribute to the growing research stream of understanding team leadership from the network approach (Carter et al., 2015). Social network literature provides important theoretical and practical insights to understand the impact of leadership activities on team performance (Kilduff & Krackhardt, 2008; Klein, Lim, Saltz, & Mayer, 2004; D. J. Krackhardt, 1999). The notion of team leaders obtaining network resources that benefit work teams has been established for a decade (Balkundi & Harrison, 2006; Balkundi & Kilduff, 2006). Yet it remains unclear when such network resources of team leaders are more or less advantageous. Centrality or central positions in any network represent, in essence, only the intensity of position holder's connectivity. Such connectivity might be less favored when it refers to negative connections, less important connections, or when team members have lower needs of leadership interventions. By testing the moderating role of team size in both advice-giving and advice-receiving networks, we provide a fine-grained picture of when team leader centrality is beneficial, unrelated, or even detrimental to team performance. In line with the longstanding wisdom of emphasizing the importance of performance contexts for team leaders to fulfill their functions in leadership literature (Day et al., 2006; Zaccaro et al., 2001), our study responds to the increasing call in social network literature to take into account structural characteristics of team networks when analyzing the impacts of leaders' network resources in social network literature (Kilduff & Balkundi, 2011; Sparrowe et al., 2001). This study, therefore, invites future studies to further examine other contextual factors for team leaders to deploy their network resources, including but not limited to structural characteristics of team networks.

Extending from this contingent view, our study also contributes to understanding how team leaders make use of such network resources to the maximum utility in team processes, by investigating the influential mechanisms (subordinate collaboration vs. leader's sense of power) of such moderated effects in specified networks. Such exploration was very scarce in the past decades (Balkundi et al., 2011). Our study directly tested the mediating role of subordinate coordination in the advice-giving networks and found no empirical support for subordinate coordination translating the positive influence of leader centrality on team performance of large teams. But, interestingly, the negative influence of leader centrality on the performance of small teams was indeed found to be mediated by subordinate coordination that, central leaders distract subordinates from coordinating with each other in small teams and thus hinder team performance. One explanation might be that central leadership works through one-to-one guidance and coordination and therefore does not necessarily bind all subordinates together. As indicated in social network literature, individuals who receive connections from the central members do not necessarily connect with each other (i.e., transitivity effect, Snijders, 2001). Given that this assumption of team leaders improving team processes via their centralized network resources prevailed in prior studies (Balkundi & Kilduff, 2006; Balkundi et al., 2011; Kratzer et al., 2008; Mehra, Dixon, et al., 2006), it is of great importance to continue exploring what translates the positive impacts of leader centrality.

We also examined and supported the mediating role of leader's sense of power along the moderated effect of leader centrality in the advice-receiving networks. The resource of receiving upwards suggestions was much neglected in prior network studies on team leadership, as most studies assumed a one-way influence that team leaders intervene subordinate functions rather than receive advice from followers (Kratzer et al., 2008; Mehra, Dixon, et al., 2006). Yet, as indicated in our findings, the moderated impact of leader centrality in the advice-receiving networks tends to lower leader's sense of power and therefore inhabits team performance. Prior studies, conceptually or empirically, considered how network resources of team leaders shape followers' perceptions (e.g., Balkundi et al., 2011). With this influential path, our study clearly points out the indispensable role of team leaders' psychological states in understanding how team leaders make use of their network resources in teams. This invites future research to take into account not only how team members react to leader's network resources but also how team leaders themselves react to their network roles and impacts.

Practical Implications

Our study also has implications for managerial practices. While previous studies recommended placing designated leaders in the center of team networks (Balkundi & Harrison, 2006), our findings point to flexible positions of leaders in directed advice networks. Team leaders ought to be more cautious to instruct subordinates to tackle task-related issues in small teams or to rely on subordinates for information and advice when placed in large teams. Alternatively, teams could consider hands-off leadership styles when appropriate. Moreover, by showing the negative impacts of leader centrality through low levels of subordinate collaboration and leader's sense of power respectively, our study also cues team leaders in central positions to compensate team dynamics by fostering collaboration and integration and active intervention to transmit such information advantages.

Limitations and Future Directions

As in all research, the choices made in this study lead to some clear limitations. First, although we measured advice network communication and team performance at different times (two weeks in between), this does not enable us to establish causality of the relationship in question. Longitudinal designs would provide more evidence concerning the causal links. Secondly, our measure of subordinate collaboration is not ideal. This variable was rated by team leaders, together with the team performance measure. Although a Confirmative Factor Analysis suggested acceptable discriminant validity from performance measure, objective and/or multi-sourced assessments would have generated more reliable results. Moreover, we obtained a general score on team collaboration with a one-item scale.

Considering team process of collaboration involves multiple stages (e.g., information exchange, information elaboration, information integration, Homan, van Knippenberg, Van Kleef, & De Dreu, 2007), future research may gain from multi-dimensional measures of subordinate collaboration.

As mentioned earlier, our focus on intra-team networks restrains us from incorporating the external functions of team leaders, which is equally important in leadership roles (Druskat & Wheeler, 2003). Enhancing intra-team collaboration is merely one part of leadership duties in teams. Effective team leaders ought to also maintain strategic connections between teams and organizations, obtain resources from the external environment, and act as ambassadors between teams and outsiders (Ancona, 1990; Ancona & Caldwell, 1992). Yet the external function of team leaders has been insufficiently attended, particularly from the social network perspective. Future work should extend the role of leader centrality to inter-team networks. It is also intriguing to test how leaders leverage inter-team connections to stimulate subordinate collaboration and team performance. Extending to inter-team networks would enable us to explore more strategic positions of team leaders. For example, besides the central position in a team network, brokerage role represents another vital position for individual players to maneuver in network dynamics (Burt, 2004; Fleming & Waguespack, 2007). It allows position holds to access to both inward and outward view and information sources, while central/core position emphasizes on merely inward communication. Many research questions can be asked following this perspective, such as when and how work teams benefit from leaders positioned in intra-team centers and inter-team brokerage roles respective?

Conclusion

The advance of social network theories fuels the research body of team leadership research. Central to understanding how teams benefit from leaders' embeddedness in team networks are the questions of when and how team leaders leverage their network resources to boost their leadership functions. In response to these questions, we examined the conditional impacts of leader centrality on team performance across different team sizes in the advice-giving and advice-receiving networks respectively and further explored the underlying mechanisms of such moderated effects. Our findings and evidence speak to the importance of taking into account the contextual inputs of network characteristics and how such effects get transmitted via both team members and team leaders.

Chapter 5 General Discussion

Throughout this dissertation, team creativity has been defined as the collective generation of novel and useful solutions to organizational problems in work teams (Amabile, 1988b; Perry-Smith and Shalley, 2003; Hargadon and Bechky, 2006; Shalley and Zhou, 2008). The context of work teams features social interdependence and intricate dispositions, which greatly complicate the development of collective creative solutions. Individual creative resources must be strategically composed and aligned (e.g., Humphrey & Aime, 2014; Mathieu et al., 2014), and diversified social activities add to the interpersonal complexity of team creative processes (van Knippenberg, 2017; van Knippenberg & Mell, 2016), and institutionalized social patterns influence how creative resources embedded in team structures get deployed (Humphrey et al., 2009; Kratzer, Leenders, & van Engelen, 2010; van Knippenberg & Mell, 2016). More importantly, the coexistence and interdependence of these diverse inputs call for an integrative rather than isolated view on how team creativity emerges within the organizational turbulence. As introduced in Chapter 1, this dissertation, therefore, proposes an integrative view to understand the development of team creativity, combining three major perspectives of the individual difference perspective, collective process perspective, and the social network perspective.

By combining different theoretical perspectives and methodological strategies, this dissertation presents three empirical chapters to understand how team creativity and team performance in general emerge from individual inputs embedded in social network structures. Although Chapter 4 discusses general performance rather than creative performance in teams, the logic presented there is consistent with the overall picture.

Summary of Main Findings

Chapter 2: Integration of Composition Model, Process, and Matching Structure

Chapter 2 focused on a theoretically significant yet empirically underrated composition model—the disjunctive model. By integrating this disjunctive model with collective information processes embedded in a team's subgroup structure, I found that team creative performance is more positively related to the highest individual creativity when the subgroup surrounding the most creative member(s) is less apt at information elaboration than more.

The logic behind this "counterintuitive" finding is built upon two lines of reasoning. First, when information elaboration is low, collectives tend to rely on inputs from their most capable members (Morrison & Vancouver, 2000), and in turn convert such inputs into team solutions with less alternation, because high information elaboration synergizes all available inputs including both creative and mediocre ideas, and eventually pulls the final solutions towards average ideas in order to cover all (van Knippenberg et al., 2004). In other words, creative star member's inputs are more likely to be selected and retained in their original form in determining team creativity in low information elaboration condition. Secondly, the prevalence of subgroups divides and segregates information processing in work teams, and makes it inaccurate to examine information elaboration of the overall team (Lau & Murnighan, 1998; Levine & Moreland, 1998; van Knippenberg & Mell, 2016). Hence, in work-related communication networks—and advice-giving networks more in particular—the actual information elaboration of the most creative members' inputs is more likely to occur in their immediate subgroup. Such a model consolidates the disjunctive model that has been understated in team creativity literature, while highlighting its contingencies, in particular information elaboration in the subgroup around the creative star of a team.

In addition to positing this Disjunctive-Elaboration Model, we also found, using this same moderation model, that the widely recognized positive effect of information elaboration takes place only when the absolute creativity level of a work team's most creative member is low as opposed to high. In other words, the effects of the most creative member's creativity and of teamwork substitute each other in predicting team creativity. This substituting effect of information elaboration and highest individual creativity echoes van Knippenberg and Hirst's (2015) suggestions that creativity researchers need to take into account different types of interplay between persons and contexts. Our findings imply that team dispositions and contextual inputs as predictors of team creativity may have more complex interactions than them simply working tandem.

Chapter 3: Validity and Contextual Boundaries of Different Aggregation Models

Chapter 3 provided meta-analytic evidence for the validity of the two most theoretically relevant aggregation models of team creativity—the additive model and the disjunctive model—as well as for their boundary conditions, both on the micro level and macro level. As our results reveal, both the average individual creativity (i.e., the additive model) and the highest individual creativity (i.e., the disjunctive model) correlate positively, and roughly equally strongly, with team creativity. Moreover, reflecting a logic of creative and mediocre inputs mingling probabilistically, the predictive power of the additive model was found to vary across team performance environments, such that the additive model is more predictive of team creativity when creativity task demands in teams are low rather than high, and also when teams work in low-tech than in high-tech industries. Conversely, the predictive power of the disjunctive model did not vary across performance environments, implying that relying on the most creatively capable member is an efficient strategy. It indicates that the theoretically significant yet empirically underrated disjunctive model indeed has an equally solid and even more reliable effect on team creativity as the established additive model.

Chapter 4: Contingent Impacts and Influential Mechanisms of Leader Centrality in Team Networks

Whereas Chapter 2 and 3 examined how intra-team compositions and collective process embedded in network structures jointly foster team creativity, Chapter 4 outlines a field project examining from a social network perspective how the external information dynamics between work teams and designated team leaders shape team performance from a social network perspective. Even though the focal outcome of Chapter 4 is team performance instead of team creativity, it similarly advances our understanding of the conceptual framework of team emergence, as team creativity is one specific form of team performance, and team leadership has a general impact on both routine tasks (i.e., team performance) and complex cognitive tasks (i.e., team creativity). In line with our hypotheses, this study found that the role of leader centrality on team performance is subject to team size and the nature of advice networks (i.e., the advice-giving network vs. the advice-receiving network). More specifically, leader centrality only promoted team performance in the advice-receiving networks of large teams, but impeded team performance in the advice-giving network of small teams, and in the advice-receiving network of large teams. We further looked at the influential mechanisms of leader centrality under different conditions by testing two mediated moderation models. Subordinate collaboration partially mediated the interaction between team size and leader centrality in the advice-giving network. More specifically, leader's centrality in the advice-giving network impedes subordinate collaboration which, in turn, impairs team performance, but only in small teams and not in large teams. On the other hand, leader's sense of power mediated the interaction between team size and leader centrality in the advice-receiving network.

Theoretical Implications for Team Research

The findings of these three empirical chapters advance the research stream of team creativity towards a more fine-grained and integrative view of how team creativity develops from creative dispositions, cognitive processes, and social structures in work teams. The implications of these findings can also be applied to team research in general. Whereas each empirical chapter ended with more detailed and focused discussions of theoretical and practical relevance, this section takes a "macro" view to discuss the general implications of the findings of each of these three projects.

One major contribution lies in the investigation of complex composition models. These models have been proposed since long, but remained underexplored until recent years (Humphrey & Aime, 2014; Kozlowski & Bell, 2003; Kozlowski & Klein, 2000). After decades of using the additive model, by default, to aggregate team members' dispositions on the team level, scholars are now challenging the assumption of homogeneous contributions of individual inputs to team success (Bell, 2007; Bell, Villado, Lukasik, Belau, & Briggs, 2011; Humphrey & Aime, 2014). Some individuals may contribute disproportionally to team outputs, such as the disjunctive model that explains team outcomes from the most capable member's inputs (Schilpzand, Herold, & Shalley, 2011; Taggar, 2001). This dissertation supported and further extended the disjunctive model of team creativity to a model that takes into account the contexts of team processes, task features, and industrial settings (Chapter 2, 3), and also provided preliminary evidence of the additive model in predicting team performance (Chapter 4). More importantly, meta-analytic evidence showed that the additive and disjunctive model predicted team creativity equally well (Chapter 3), demonstrating the value of not only the predominant additive model but also the underrepresented disjunctive model. This brings the disjunctive model for the first time to the fore in team composition research, and more importantly, raises questions about the interplay of composition models and team performance environment. Team outcomes emerge from not only the combination of individual inputs, but also the fit between composition logic (e.g., the disjunctive model) and task requirements, team structure, team functioning, and other contextual factors (Kozlowski & Klein, 2000). Understanding the validity of different composition models also requires further exploration of how the performance environment shapes when and how teams deploy different composition models.

This dissertation also advances the research body of collective processes. It examined the role of collective processes in different forms, as a contextual force (i.e., subgroup information elaboration) to retain the star impact on team creativity (Chapter 2), or as both a subordinate and a leadership process to directly translate central leader's influence on team performance under different conditions (Chapter 4). Chapter 2 responds to the recent call for empirical tests on divided subgroup processes (van Knippenberg & Mell, 2016). Despite the ubiquitous subgroups in team information processes (Su, Huang, & Contractor, 2010), prior studies tended to assume unitary team processes that indiscriminately involve every team member. The findings of Chapter 2, therefore, advance this line of exploration and invite future studies to test how team processes vary across different subgroups. More importantly, our finding that the influence of individual dispositions (i.e., star member creativity) and the influence of collective processes (i.e., subgroup information elaboration) substitute each other underlines the significance of an integrative view that considers team inputs and team processes simultaneously. Chapter 4, on the other hand, contributes to the literature of team processes by zooming in on how one significant player—team leader—influence team performance via the subordinate process and leadership process separately. This offers a more refined view into identifying how heterogeneous inputs convert into team outputs. This again speaks to the growing need for integrative views that combine the perspective of team processes with the perspective of team characteristics such as individual dispositions and team communication structures.

Using a social network perspective, this dissertation contributes to team research not only through a specialized understanding of collective processes embedded in team structures (Chapter 2) but also through a direct examination of the impacts of network structures on team outputs (Chapter 4). Social network theories have been increasingly applied in team research to understand both the overall team structures (Leenders et al., 2003) and the network positions of particular team members, such as team leaders (Balkundi & Harrison, 2006). Yet the social network approach had not yet been deployed to understand the subgroup dynamics in prior studies. As more attention is being paid to the divided communication patterns in subgroups, recent studies have examined the subgroup structures either by manipulating faultline patterns in laboratories (e.g., Pearsall, Ellis, and Evans, 2008) or by measuring the subgroup strength with the latest diversity-based algorithms (Xie, Wang, & Qi, 2015). Chapter 2 highlights the advantage of using social network methods to identify heterogeneous social relational patterns in subgroups that are otherwise difficult to capture with traditional research methods. This allows future studies to continue the exploration of complex subgroup dynamics in an integrative and refined manner.

Conclusive Remarks

Team creativity is a main driver of corporate competitive advantages for today's business. To understand the emergence of team creativity, scholars have extended the theories of individual creativity to the team level and have identified plenty of factors from the perspectives of team dispositions, collective processes, and structural patterns. Yet the absence of integrative views makes that most empirical efforts are oversimplifications. With longstanding methodological tools to clearly identify embedded relational patterns and processes in great details, the social network perspective can move team creativity research towards a high-resolution view, and thus has had great appeal to creativity scholars in the past two decades. Employing social network tools, this dissertation presented empirical evidence for (a) when creative star member's individual inputs shape team creativity, (b) when different dispositions models explain team creativity under different performance contexts, and (c) how external leaders embedded in team networks determine team performance. While advancing our understanding of team creativity each of these empirical projects also raises new questions for future research to further explore how team creativity emerges from heteronomous individual inputs.

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SUMMARY

To continually succeed in today's turbulent business environment, organizations increasingly deploy teams and build their competitive advantages on the inimitable capital of creativity. The emergence of team creativity is therefore of practical and theoretical interest, and has been explored through three major perspectives in the past decades: creative individual dispositions, collective processes that synergize individual resources, and team structures that determine the social patterns within teams. Yet prior empirical endeavors often oversimplify these perspectives, assuming the homogeneous contributions of all individual inputs to team creativity or equal participations in creativity-relevant team processes. With the social network perspective, this dissertation addresses this question of insufficient heterogeneity and provides a more fine-grained picture of these three perspectives of team creativity. Moreover, the three empirical chapters in this dissertation present an integrative view of how these three different perspectives jointly determine the emergence of team creativity.

The first empirical chapter extends our understanding of the conceptually sound yet underrepresented disjunctive model of team creativity—predicting team creativity with the highest individual creativity, adopting the social network perspective to observe the interplay between creative individual dispositions and collective information processes in teams. Using multi-source data from 60 franchised bakeries (483 employees and 60 team managers) in China, this study showed that a team benefits from the creativity of the most creative member only when the information elaboration in the subgroup surrounding this member is low rather than high. Interestingly, the results reveal substituting effects of the

most creative member and subgroup information elaboration, such that the positive impact of subgroup information elaboration on team creativity only holds when the most creative member is less creative in an absolute sense.

The second empirical chapter tests the predictive power of two major aggregation models of team creativity—the additive model (i.e., team creativity is subject to the sum of individual creativity) and the aforementioned disjunctive model of team creativity, and examines the moderating roles of creative task demands and industrial background (low-tech vs. high-tech) through a meta-analysis. Based on 114 empirical studies published between 1980 and 2015, this study demonstrates that both the additive and disjunctive models explain team creativity, with similar effect sizes. More specifically, the additive model is more predictive under the condition of low creative task demands and also under the condition of low-tech industries, whereas the disjunctive model holds across different conditions of both creative task demands and industrial background.

The third empirical chapter provides insights from a social network perspective into when and how leader centrality (i.e., the extent to which an individual holds the most connections in a network) impacts team performance. With a dataset of 552 employees and 72 team leaders from 72 franchised bakeries in China[7], this study extends our understanding of when leader centrality benefits team performance. In teams of more than 12 members, leader centrality is beneficial in advice-giving networks but detrimental for advice-receiving networks, whereas in teams of less than 8 members, leader centrality is detrimental in advice-giving networks but does not affect performance in advice-receiving networks. Two influential, independent mechanisms are explored to explain such interactions: subordinate

[7] This chapter uses the same data set as the first empirical chapter, but different variables.

collaboration in advice-giving networks and leader's sense of power in advice-receiving networks.

Together, these empirical studies advance the field of team creativity by providing a more refined and integrative account of its predictors. These findings offer practical implications for managers to strategically deploy creative individuals and leverage their contributions with proper collective processes and leadership inputs. This dissertation also raises up questions for future studies to further our understanding of the emergence of team creativity.

SAMENVATTING

Om in de huidige turbulente zakenwereld voortdurend succes te behalen, hanteren bedrijven steeds vaker teams, en baseren ze hun concurrentievoordeel op een onnavolgbare vorm van kapitaal: creativiteit. Het verschijnsel teamcreativiteit spreekt daarom zowel geleerden als praktijkmensen aan, wat in de afgelopen decennia heeft geleid tot drie belangrijke perspectieven om het ontstaan van teamcreativiteit te verkennen: creatieve individuele disposities, collectieve processen die individuele middelen samenvoegen tot meer dan de som der delen, en teamstructuren die de sociale patronen in teams bepalen. Eerdere empirische studies oversimplificeren echter deze perspectieven door homogene bijdragen van individuen aan teamcreativiteit te veronderstellen of gelijke deelname aan creativiteitsrelevante teamprocessen. Deze dissertatie hanteert een sociaal netwerk perspectief om de kwestie van onvoldoende heterogeniteit aan te pakken en geeft een fijnmaziger beeld van deze drie belangrijke perspectieven. Verder bieden de drie empirische hoofdstukken in deze dissertatie een integratieve kijk op hoe deze drie verschillende perspectieven tezamen het ontstaan van teamcreativiteit bepalen.

Het eerste empirische hoofdstuk bekijkt vanuit een sociaal netwerk perspectief het samenspel van creatieve individuele disposities en collectieve informatieprocessen in teams om zo meer begrip te verkrijgen van het conceptueel logische maar ondervertegenwoordigde disjunctieve model van teamcreativiteit, welk teamcreativiteit voorspelt aan de hand van het meest creatieve teamlid. Door middel van multi-source data van 60 franchisebakkerijen (483 werknemers and 60 team managers) in China liet deze studie zien dat een team alleen voordeel haalt uit de creativiteit van het creatiefste teamlid wanneer de informatie-uitweiding in de subgroep rondom dit teamlid laag in plaats van hoog is. Interessant genoeg onthullen de resultaten ook een substitutie-effect van het creatiefste groeplid en informatie-uitweiding van diens subgroup, zulks dat het positieve effect van de informatie-uitweiding van een subgroep op teamcreativiteit alleen geldt wanneer het creatiefste lid in absolute zin niet buitengewoon creatief is.

Het tweede empirische hoofdstuk test het voorspellende vermogen van twee belangrijke aggregatiemodellen van teamcreativiteit—namelijk het eerdergenoemde disjunctieve model, en het additieve model waarin teamcreativiteit afhankelijk is van de som van individuele creativiteit. In het bijzonder wordt door middel van een meta-analyse de modererende rol bekeken van creatieve taakvereisten en industriële achtergrond (low-tech vs. high-tech). Op basis van 114 empirische studies gepubliceerd tussen 1980 en 2015 demonstreert deze studie dat zowel het additieve model als het disjunctieve model teamcreativiteit verklaren, met vergelijkbare effectgroottes. Meer specifiek is het additieve model vooral een goede voorspeller wanneer sprake is van lage creatieve taakvereisten en van low-tech industrieën, terwijl het disjunctieve model geldig is ongeacht de aard van de creatieve taakvereisten en industriële achtergrond.

Het derde empirische hoofdstuk biedt middels een sociaal netwerk perspectief inzichten in wanneer en hoe de centraliteit van een teamleider (ofwel de mate waarin een teamleider de meeste connecties heeft binnen een netwerk) teamprestaties beïnvloedt. Door middel van een dataset van 552 werknemers en 72 teamleiders van 72 franchisebakkerijen in China[8] vergroot deze studie ons begrip van wanneer de centraliteit van een teamleider teamprestaties verbetert. In teams van meer dan 12 leden is leidercentraliteit voordelig in

[8] Dit hoofdstuk gebruikt dezelfde dataset als het eerste empirische hoofdstuk, maar andere variabelen .

adviesgevingsnetwerken maar nadelig in adviesontvangstnetwerken, terwijl in teams van minder dan 8 leden leidercentraliteit nadelig is in adviesgevingsnetwerken maar teamprestaties niet beïnvloedt in adviesontvangstnetwerken. Twee invloedrijke, onafhankelijke mechanismen werden verkend om deze interacties te verklaren: samenwerking van ondergeschikten in adviesgevingsnetwerken en het gevoel van macht van een leider in adviesontvangstnetwerken.

Tezamen stuwen deze empirische studies het veld van teamcreativiteit voort door een meer genuanceerde en integratieve uiteenzetting te verschaffen van predictoren van teamcreativiteit. Deze bevindingen bieden managers praktische implicaties om creatieve individuen strategisch in te zetten en hun contributies the benutten door middel van geschikte collectieve processen en inbreng van leiders. Tenslotte werpt deze dissertatie voor toekomstige onderzoek vragen op die ons begrip van het ontstaan van creativiteit kunnen vergroten.

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Yingjie Yuan (1987) was born in Shishou, Hubei, China. She joined ERIM and started her Ph.D. at Rotterdam School of Management in 2012 and was a visiting Ph.D. at Pennsylvania State University in 2015. Before that, she obtained a Master of Science Degree from the Renmin University of China, China, majored in Organizational Behaviors. Yingjie also holds two Bachelor's degrees in Information Management (major) and Economics (minor) from Wuhan University, China. Currently, she is an Assistant Professor of Human Resource Management & Organizational Behavior at the University of Groningen, the Netherlands.

Yingjie's research lies at the intersection between team creativity and social networks in organizations. Her dissertation examines the emergence of team creativity from the composition models of individual creative sources embedded in network structures. Her research was presented at various international conferences including the Academy of Management, Interdisciplinary Network for Group Research, International Network for Social Network Analysis, and International Association for Chinese Management Research.

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To overcome complex and dynamic economic challenges, organizations increasingly employ teams and build their competitive advantages on the inimitable capital of creativity. Naturally, when and how individual inputs combine to form team outcomes has therefore become one of the core questions in developing creativity theories. For years, empirical studies have been based on the assumptions of the additive model, where individual team members contribute equally to team creativity. This dissertation challenges this assumption in different ways. In the first empirical chapter, I provide evidence for an alternative model, the disjunctive model, which predicts team creativity based on the creative performance of a team's most creative member, and shows under which conditions this most creative member's inputs are adopted and contribute to team creativity. The second empirical chapter meta-analyzes the validity of both the additive model and the disjunctive model, and finds support for both across different contexts. The third empirical chapter extends the focus from a team's creative performance to a team's general performance, and uses a social network perspective to examine how the 'disjunctive' role of team leaders promotes team performance. The core contribution of this dissertation lies in supporting the predictive power of the disjunctive model of team creativity, thereby challenging mainstream research on team creativity which undervalues the importance of key team members and their surrounding subgroups. A contingent perspective on both additive and disjunctive models is proposed.

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