The network-performance relationship in knowledge-intensive contexts – A meta-analysis and cross-level comparison

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Abstract

This study examines the generalizability of the network-performance relationship across individual and group levels, focusing on knowledge-intensive contexts. Drawing on a meta-analytical approach, we synthesize the results of 102 empirical studies to test whether network characteristics such as centrality, brokerage, and tie strength similarly influence the job performance of individuals and groups. Results show that while there are no differences in the direction of the network-performance relationship across levels, there are substantial differences in magnitude. Individual performance profits more strongly from a high number of direct connections, whereas groups reap higher benefits from brokerage positions. Additional analyses reveal that the network measurement method, tie content, and performance criteria function as moderators of the network performance relationship, but their influence is neither consistent across network characteristics nor across levels. By meta-analytically comparing and contrasting the network-performance relationship for individuals and groups, we contribute to multilevel research on networks and organizations. Particularly, we move towards the development of a multilevel homology theory of networks. Implications for theory, practice, and future research are discussed.

Keywords: individual network, group network, job performance, meta-analysis, multilevel

Introduction

Researchers and practitioners alike have long recognized the beneficial influence of network embeddedness on performance at different organizational levels, particularly in knowledge-intensive contexts (e.g., Burt, 2004; Cross, Kaše, Kilduff, & King, 2013; Keller, 2001). At the individual level, recent meta-analytic summaries of several decades of research have shown that a central network position, brokerage, and strong ties are crucial determinants of job performance and innovativeness (Baer, Evans, Oldham, & Boasso, 2015; Fang et al., 2015). With the rise of teamwork in organizations, scholars increasingly investigate the network-performance relationship also at the level of the group, focusing on groups' external networks to other groups (e.g., Kratzer, Leenders, & van Engelen, 2010; Tsai, 2001). Their basic assumption is that in today's complex environment single groups – just like single individuals – are no longer able to possess all the relevant resources needed to succeed and can reap performance benefits from networks (e.g., Ancona & Caldwell, 1992; Marrone, 2010).

A review and comparison of research conducted at the individual level and group level highlights that studies at both levels largely apply the same network theoretic constructs and their empirical associations to predict performance (Borgatti & Foster, 2003; Moliterno & Mahony, 2011). In other words, a certain network position of employees in a co-worker network allegedly has the same effect on employee job performance as the respective position of groups in an inter-group network has on group performance. More than that, it seems to be common practice to refer to studies conducted at the individual level when the actual object of analysis is the group and vice versa (e.g., Lechner, Frankenberger, & Floyd, 2010; Zaheer & Soda, 2009), often without explicitly pointing out the cross-level inference made. In short, research on the network-performance relationship in organizational contexts seems to be guided by the implicit assumption that the influence of network embeddedness on performance is generalizable – or homologous (Chen, Bliese, & Mathieu, 2005a) – across levels. However, we have yet to test the homology assumption empirically. Neglecting to do so and merely assuming generalizability, scholars risk oversimplifying their theoretical model and committing a cross-level fallacy (Rousseau, 1985), and practitioners may draw flawed conclusions about which network structures to foster at each level within their organization.

The purpose of this study is to test the generalizability of the network-performance relationship for individuals and groups. To this end, we conduct a meta-analysis and examine whether the level of theorizing moderates the influence of network embeddedness on job performance. This approach not only enables us to validate within-level findings across a large set of studies, but also allows us to identify network-theoretic relationships that are not homologous across individual and group levels (Moliterno & Mahony, 2011). Our study focuses on research conducted in knowledge-intensive contexts where networks are especially important for individuals and groups to succeed due to high degrees of task interdependence and complexity (e.g., Reagans & McEvily, 2003). We investigate centrality, brokerage, and tie strength as key characteristics of instrumental as well as expressive networks that the majority of past research on the network-performance relationship at either level has analyzed. We examine the influence of these network characteristics on job performance of individuals and groups, defined as success in completing tasks and responsibilities in a given role (Fang et al., 2015). To investigate the generalizability of our findings not only across levels, we additionally analyze the influence of meaningful moderators on the network-performance relationship.

Exploring whether the network-performance relationship is generalizable across levels, we contribute to multilevel research on networks and organizations. Particularly, we add to the development of a multilevel homology theory of networks in knowledge-intensive contexts. While there have been calls in the literature to analyze the cross-level generalizability of relationships for some years now (Kozlowski & Klein, 2000; Payne, Moore, Griffis, & Autry, 2011; Phelps, Heidl, & Wadhwa, 2012), there are, to the best of our knowledge, no studies taking on this task with respect to organizational networks. Examining whether different network characteristics vary in their influence on job performance depending on the level of theorizing, we are able to refine the scope of the network-performance relationship and improve our understanding of cross-level differences in organizations (Chen et al., 2005a). Moreover, our study contributes to existing research by meta-analytically synthesizing the empirical literature on the impact of individual-level and group-level networks on performance with a particular focus on knowledge-intensive contexts. In a research area such as organizational networks, that has produced a large body of publications in the past 30 years, meta-analysis provides the means to consolidate the often conceptually different studies and discover common patterns within and across levels.

Theory and Hypotheses

Homology: The Network-Performance Relationship across Organizational Levels

In multilevel research, the term "homology" describes the notion "that constructs and the relationships linking them are generalizable across organizational entities" (Kozlowski & Klein, 2000: 44). Homology thus rests on two basic assumptions. First, individual constructs used in a model have theoretical similarity across levels (Chen et al., 2005a; Rousseau, 1985). A certain network characteristic captured at the level of individuals and groups needs to have a similar meaning at both levels to make a cross-level comparison of its effects meaningful. With respect to their measurement, network characteristics fulfill this assumption. Network theoretic constructs such as centrality, brokerage, and tie strength investigated in this study are by definition scale invariant concerning levels of analysis (Moliterno & Mahony, 2011) and can be applied to various types of networks and actors (Wasserman & Faust, 1994). Yet, Chen et al. (2005a) point out that it is not simply a question of measurement but foremost a theoretical question whether constructs have consistent conceptual meanings across levels. It is not sufficient to measure network characteristics, such as centrality, using the same metrics (e.g., degree centrality; Wasserman & Faust, 1994) independent of the type of network under investigation. Rather, there need to be strong theory-based arguments to assume that networks fulfill the same function at different organizational levels. For instance, ties serve as conduits for resources (e.g., Borgatti & Halgin, 2011; Sparrowe, Liden, Wayne, & Kraimer, 2001) and prisms to distribute information and exert influence (Podolny, 2001) at the level of individuals and the level of groups. At both levels, they also function as constraints to individuals' and groups' agency (Brunetta, Boccardelli, & Lipparini, 2015; Granovetter, 1985). Likewise, job performance exhibits theoretical similarity across levels because it is the assessment of qualitative and quantitative aspects of task accomplishments for individuals as well as groups.

Network characteristics and performance displaying theoretical similarity across levels is a necessary but not sufficient condition for the network-performance relationship to be homologous. The second assumption underlying homology emphasizes that relationships among constructs observed at different levels also need to be comparable across organizational entities. This assumption directly pertains to the purpose of our study, namely, analyzing whether the network-performance relationship is generalizable across the individual level and the group level or whether the level of theorizing functions as a moderator of the relationship. To approach this question, we focus on centrality, brokerage, and tie strength, and discuss the impact of these network characteristics on performance at the level of individuals and groups.

Network Centrality and Performance

Direct Connectedness. In its simplest form, network centrality is determined by the number of direct network connections (Freeman, 1979), that is, the number of other individuals tied to a person or the number of other groups connected to a group. Concerning individuals, many direct connections imply timelier access to more and alternative resources, such as information and support (e.g., Anderson, 2008; Moran, 2005). These resources trigger learning and enable individuals to combine existing knowledge with new information, thereby boosting performance in knowledge-intensive contexts (Burt, 2004; McFadyen & Cannella, 2004). As a drawback, individuals with many ties may be so busy establishing and maintaining their network that their performance suffers (McFadyen & Cannella, 2004). Despite the latter point, we expect the benefits of direct connectedness to be more potent in knowledge-intensive contexts where new and diverse information plays a critical role in driving individuals' innovativeness and performance (Fleming, 2001). Managers in these contexts are increasingly encouraged to establish cultures of exchange and provide the necessary time for employees to sustain network ties (Cross et al., 2013; Hauschild, Licht, & Stein, 2001) so that maintenance costs should not carry much weight. Recent meta-analytic findings provide empirical backup for this assertion, confirming a positive relationship between direct connectedness and performance at the individual level (Baer et al., 2015; Fang et al., 2015).

At the group level, group-external ties to other groups equally function as conduits for diverse and novel knowledge and information (e.g., Kratzer et al., 2010; Wong, 2008). As tasks are complex and even groups that combine the expertise of all of their members often do not possess all the means needed to succeed, access to external resources is of high importance especially in knowledge-intensive contexts (e.g., Ancona & Caldwell, 1992; Hansen, 2002). Moreover, because group members are able to divide tie creating and maintaining activities among them, groups are better able than individuals to effectively manage a high number of direct connections and thus perceive them to be less time-consuming and distracting (Oh, Labianca, & Chung, 2006). In line with this reasoning, empirical studies at the group level overwhelmingly find a positive direct connectedness-performance relationship (e.g., Balkundi & Harrison, 2006; Cummings & Haas, 2012; Kratzer et al., 2010).

As becomes clear, theoretical arguments and empirical findings for the influence of direct connectedness on performance evolve along similar lines, independent of the level of theorizing, thus confirming the homology assumption. Individual-level and group-level studies alike emphasize the benefits of having timely access to a high number of resources that are likely to outweigh the maintenance costs of direct connections in knowledge-intensive contexts. In sum, we therefore expect a positive direct connectedness-performance relationship at both levels:

> *H1: At the individual level and the group level, direct connectedness will have a positive influence on job performance.*

Global Connectedness. Apart from direct connections, indirect connections function as important antecedents of job performance (e.g., Mote, 2005; Perry-Smith, 2006) and bring about distinct benefits and costs. Measures of centrality that take into account indirect connections build on the entire network of an individual or group. Thus, they capture "global connectedness" (Perry-Smith & Shalley, 2003). At the individual level, high global connectedness can lead to a better understanding of what is going on in the network (Perry-Smith, 2006). Moreover, "direct and indirect ties provide access both to people who can themselves provide support and to the resources those people can mobilize through their own network ties" (Adler & Kwon, 2002: 24).

Finally, high global connectedness implies independence, as individuals do not have to rely on intermediaries to connect with others. It also implies efficiency as they can reach their network connections on short paths, which is beneficial with respect to the distribution of information and the exertion of influence (Brass, 1984; Freeman, 1979). As possible constraints going along with high global connectedness, Perry-Smith and Shalley (2003) mention information overload and maintenance costs. Following the same context-based reasoning as above, we however expect these costs to be outweighed by the benefits that high global connectedness brings about for knowledge-intensive work. Empirical evidence for this assertion comes from Ibarra (1993) – among others – who shows that global connectedness positively affects individuals' innovative performance.

Concerning groups, scholars similarly focus on the improved reachability of other groups enabled by high global connectedness. For instance, investigating inter-unit relations Hansen (2002) observes that search activities are more efficient and information is less distorted if it can be attained via fewer intermediaries. As shortcomings, Brunetta et al. (2015) argue that high global connectedness may lead to an unwanted drain of information and to augmented coordination costs that may hamper group performance. Information losses resulting from global connectedness can be seen as the flipside of distribution advantages emphasized by individual-level scholars. We reason that while global connectedness may cause both of these outcomes, the importance of protecting confidential knowledge to secure competitive advantages is a salient issue in knowledge-intensive contexts (e.g., Bouty, 2000). Hence, individuals as well as groups will consciously decide which information to share within their networks. Moreover, while augmented coordination may be necessary for groups to internally handle the benefits of global connectedness, groups – as compared to individuals – have a higher capacity to create short network paths by involving all of their members in tie creation, which may compensate for coordination losses. In sum, we therefore expect the benefits of global connectedness resulting from improved reachability to outweigh its potential costs, also at the group level, and propose:

> *H2: At the individual level and the group level, global connectedness will have a positive influence on job performance.*

Brokerage and Performance

Brokerage has attracted a lot of attention from scholars investigating the network-performance relationship. A broker is an individual or a group that connects unconnected or heterogeneous third parties in a network and is thereby able to benefit from advantages concerning the acquisition of resources and the dissemination of information (Burt, 1992). In the following, we distinguish between a structural and a relational approach to brokerage. While the structural approach focuses on patterns of ties in a network, the relational approach takes into account the quality or content of ties (Nahapiet & Ghoshal, 1998).

Structural Holes. Scholars following the structural approach assess brokerage by capturing individuals' or groups' tendencies to bridge structural holes, as opposed to forming dense networks characterized by closure. Bridging a structural hole means creating ties to unconnected third parties (Burt, 1992), while forming dense networks implies that the third parties in one's network will also be connected. Thus, structural holes and closure can be seen as two ends of a continuum (e.g., Battilana & Casciaro, 2012; Obstfeld, 2005). At the individual level, structural holes and closure have both been associated with performance-benefits. Individuals bridging structural holes can first profit from access to diverse, non-redundant information and second, have the possibility to control the flow of information between the third parties they connect (Burt, 2005). With respect to control, bridging structural holes can be seen as the counterpart of high global connectedness – whereby the former refers to increasing other individuals' dependence on oneself as a broker and the latter reflects a decrease of one's own dependence on others as brokers (Brass, 1984). While associated with many benefits, ties that bridge a structural hole are more time-consuming to create and require more effort to maintain (Burt, 2002). In addition, Krackhardt (1999) has highlighted that bridging positions may confront the individual with different role expectations imposed by the various third parties, all of which might hurt performance. Closure, by contrast, can benefit individuals' performance by reinforcing support, norms, and trust (Coleman, 1988). While both – structural holes and closure – have their merits for individuals, we expect that in knowledge-intensive contexts the performance benefits of structural holes outweigh those of closure. As tasks are complex and non-routine, access to heterogeneous and new information is of high importance to succeed (e.g., Fleming, Mingo, & Chen, 2007; Zou & Ingram, 2013) and should be worth the effort of tie creation and maintenance. Moreover, closure is not the only way for individuals to gain trust and support as useful resources. As we will discuss below, strong ties go along with similar benefits and particularly in knowledge-intensive contexts may be superior to closure as a means to acquire them (Levin, Walter, Appleyard, & Cross, 2015; Rost, 2011).

Studies focusing on inter-group networks largely build on structural hole theory (Burt, 1992) without explicitly addressing Coleman's (1988) notion of closure as a juxtaposition.[1] The theoretical arguments put forward with respect to structural holes at the group level resemble those discussed for individuals: Scholars emphasize the benefits of access to diverse, non-redundant information as a driver of groups' ability to handle complexity and be creative (Kratzer et al., 2010; Lechner et al., 2010). Moreover, Zaheer and Soda (2009) stress the opportunity to exploit information asymmetries between unconnected third parties, which they deem particularly important in knowledge-intensive contexts characterized not only by the necessity to cooperate but also to compete (Tsai, 2002). As a potential disadvantage, Kratzer et al. (2010) argue that the more disconnected an inter-group network is, the more distorted knowledge sharing among groups can become, making information less reliable and less rich. Just like at the individual level, we expect the benefits of bridging structural holes to outweigh these costs, also at the group level – particularly given the knowledge-intensity of the work.

In sum, the above discussion highlights that individuals and groups bridging structural holes occupy strategically advantageous positions that should be beneficial for their job performance in knowledge-intensive contexts. We acknowledge, however, that single empirical studies at both levels have found opposing results (Kratzer et al., 2010; Moran, 2005; Obstfeld, 2005) and we will discuss potential moderating influences below. Concerning the overall influence of bridging structural holes on individual and group performance, we expect:

> *H3: At the individual level and the group level, bridging structural holes will have a positive influence on job performance.*

Boundary Spanning. The relational approach to brokerage focuses on different types of pre-defined boundaries that network ties may span – in the studies we review these typically include functional boundaries within or across organizations (e.g., Cross & Cummings, 2004; Oh, Chung, & Labianca, 2004), but also boundaries created by individual or group differences, for instance with respect to knowledge (Rodan & Galunic, 2004; Zaheer & Soda, 2009). The performance benefits accruing from boundary spanning resemble those of bridging structural holes. At the individual level, boundary-spanning ties allow for the acquisition and consequent recombination of heterogeneous knowledge (Cross & Cummings, 2004; Zou & Ingram, 2013). They also offer support for the implementation of complex ideas, for instance by securing legitimacy and buy-in from different stakeholders in the organization (Rodan & Galunic, 2004). Yet, just like ties that bridge structural holes, ties spanning boundaries might be more costly to create and maintain (Burt, 2002). Again, we expect their benefits to outweigh this drawback for the reasons discussed above.

At the group level, network ties to diverse others equally allow for access to novel information and resources (e.g., Oh et al., 2004) and facilitate the transfer of best-practices (Szulanski, 1996). In addition, they enable groups to make more informed decisions (Haas, 2010) and help to avoid the dangers of groupthink (Janis, 1972; Katz, 1982). While boundary-spanning ties between groups may result in a loss of autonomy through pressure from outsiders and an increased involvement in organizational politics, they simultaneously serve as means for organizational integration and protect groups from isolation (Haas, 2010). Along with the superior access to information that they offer, we therefore expect boundary-spanning ties to be beneficial for performance also at the group level.

Empirical findings on boundary spanning corroborate our reasoning. Individual-level studies have shown that individual performance benefits from interpersonal ties crossing boundaries (e.g., Cross & Cummings, 2004; Fleming et al., 2007). Likewise, group-level studies confirm a positive impact of group boundary-spanning ties on the job performance of groups (e.g., Marrone, Tesluk, & Carson, 2007; Oh et al., 2004). Therefore, we posit:

H4: At the individual level and the group level, boundary spanning will have a positive influence on job performance.

Tie Strength and Performance

Independent of the level of theorizing, the strength of a tie is typically defined either as the frequency of interactions (e.g., McFadyen & Cannella, 2004), emotional closeness (e.g., Perry-Smith, 2006), trustworthiness (e.g., Tsai & Ghoshal, 1998), or a combination of elements (e.g., Lechner et al., 2010; Sosa, 2011). Tie strength thus captures a relational dimension of networks[2]

(Nahapiet & Ghoshal, 1998) with strong ties commonly associated with the efficient transfer of rich and complex information and knowledge (Hansen, 1999; Levin & Cross, 2004).

Concerning individuals, strong ties foster the transfer of more useful and tacit knowledge (Levin & Cross, 2004), which is of high importance for knowledge-intensive work (Swart & Kinnie, 2003). However, individuals connected by strong ties are more alike and develop similar knowledge (Reagans, 2005), which may be detrimental to their performance. As highlighted by Sosa (2011), the latter drawback may be compensated for by the various socio-psychological benefits that strong ties offer. They lead to trust and the development of norms, thereby increasing individuals' motivation to provide help, share resources, and be accessible. In addition, strong ties go along with emotional support, uncertainty reduction, and encouragement for innovative endeavors (Krackhardt, 1992; Nohria, 1992), all of which are important drivers of performance in knowledge-intensive contexts (Sosa, 2011). Empirical findings corroborate this view (e.g., Abbasi, Wigand, & Hossain, 2014; Moran, 2005).

At the group level, strong ties have been associated with similar benefits: They facilitate locating resources (Hansen, Mors, & Løvås, 2005), enable the transfer of complex and tacit knowledge (Hansen, 1999), ease task coordination (Gargiulo & Benassi, 2000), and reduce inter-group conflict (Nelson, 1989). Through these functions, they positively influence group performance (Chung & Jackson, 2013). As a potential drawback, group-level scholars have suggested that strong ties increase normative demands for reciprocation, which may distract groups and hamper performance (Lechner et al., 2010). However, as Hansen, Podolny, and Pfeffer (2001) and Reagans, Zuckerman, and McEvily (2004) have shown, strong ties actually lead to a shorter project completion time. Thus, any distractions that might result from strong ties do not seem to carry much weight, at least regarding efficiency as an important aspect of group performance.

While single empirical studies find that tie strength can be negatively related to performance (Ancona & Caldwell, 1992; Cross & Sproull, 2004) – which might be explained by moderating influences discussed below – our theoretical reasoning points toward an overall positive relationship that is homologous across levels, leading us to propose:

> *H5: At the individual level and the group level, tie strength will have a positive influence on job performance.*

Cross-Level Differences in Magnitude of the Network-Performance Relationship

The preceding discussion of the influence of different network characteristics on performance highlights that both, scholars investigating individuals and scholars examining groups, largely draw on similar arguments to justify their reasoning. The network-performance relationship hence seems to be homologous across individual and group levels, in the sense that each relationship is hypothesized to be positive and significant independent of the level of theorizing. To go a step further, we address the nature of multilevel homology by taking into account differences in the magnitude of the network-performance relationship at the levels of individuals and groups. In terms of Chen et al. (2005a) we move beyond the stage of metaphoric homology, which only considers whether relationships are consistently significant across levels, to the more mature stage of proportional homology. Proportional homology additionally takes into account whether or not the relationship under study is consistently stronger or weaker as the level of theorizing changes. Thus, it allows for more precise conclusions regarding the generalizability and the scope of a theory.

Concerning the influence of network characteristics on performance, differences in the magnitude of each relationship across levels may be due to multiple and partly opposing reasons.

They originate from the fact that individual group members enact group-level ties. In other words, even though managers and scholars attribute ties to the group as a collective, individual action is necessary for each tie to emerge and persist over time. This leads to groups having specialization advantages regarding tie-creation that single individuals do not have. As indicated above, groups can divide tie-creating activities among their members and thus establish more and more diverse network ties. In addition, they have the possibility to strategically assign specific tie-creation tasks to each member, for instance different boundary-spanning activities (Ancona & Caldwell, 1992; Oh et al., 2004). This specialization capacity might result in a higher magnitude of the network-performance relationship at the level of groups. As an additional reinforcement, it might lead to the downsides of different network characteristics having less of an impact on group performance because each member shoulders part of the burden. Through specialization, each group member may be less affected by time constraints and distractions going along with high direct connectedness. Similarly, the perceived pressure resulting from different normative demands and role expectations associated with brokerage (Krackhardt, 1999) may be smaller if every group member only creates few bridging ties on behalf of the group.

The flipside of specialization advantages for groups are coordination requirements. In order for a group to benefit from ties to other groups, its members need to be able to organize their activities. Coordination problems and other detrimental within-group processes (see for instance Steiner, 1972) may weaken any positive impact of network characteristics on performance at the group level. In addition, the performance of higher-level units such as groups or organizations has often been argued to be subject to more extraneous, confounding influences (e.g., Chen, Thomas, & Wallace, 2005b; Ployhart, 2004). A larger number of third variables affects group-level as opposed to individual-level performance. These arguments indicate that group-level networks might be less directly related to group performance than individual-level networks are to individual performance, resulting in larger effect sizes at the individual level.

The preceding line of reasoning highlights the conflicting nature of arguments regarding cross-level differences in magnitude of the overall network-performance relationship, resulting from a higher complexity at the group level. Moreover, no unambiguous conclusions can be drawn on whether potential differences in magnitude will be consistent across all five network characteristics as the notion of proportional homology proposes (Chen et al., 2005a). Given these circumstances, we propose the following research question for empirical testing:

> *Research Question: Will the network-performance relationship with respect to the different network characteristics be (consistently) stronger at the individual level or at the group level?*

Moderator Analyses

As already indicated, there are single studies that find no or even a negative influence of a specific network characteristic on performance (e.g., Ancona & Caldwell, 1992; Obstfeld, 2005). In an attempt to resolve these inconsistencies and test in how far results are independent of the study design, we investigate the role of potential moderators for the network-performance relationship. Concerning the networks under investigation, we distinguish between studies relying on primary data collected via surveys and studies relying on archival data retrieved from databases, for instance co-authorships or collaboration on patents (for a similar approach, see van Wijk, Jansen, & Lyles, 2008). As reflected by a longstanding debate in the network literature (Breiger, 1974; Marsden, 1990, 2005), this distinction might influence the network-performance relationship due to different qualities associated with the two types of network measurement. Studies relying on primary network data are typically assumed to provide a richer description of interpersonal or inter-group connections while at the same time they are prone to biases, for instance with respect to informant accuracy (Marsden, 2005). Conversely, the advantages of archival network data lie in its objectivity, accessibility, and the possibility to rely on large scale samples. Yet, scholars drawing on archival data to capture networks often have to justify in how far joint memberships, for instance in research teams, actually reflect meaningful social bonds among single individuals or groups (see the respective discussions for instance in Fleming et al., 2007; McFadyen & Cannella, 2004).

In line with prior research (Balkundi & Harrison, 2006; Fang et al., 2015) we further investigate whether tie content (i.e., instrumental vs. expressive ties) plays a moderating role for the impact of the different network characteristics on performance. While instrumental ties such as collaboration, advice seeking, or knowledge transfer are predominantly seen as pathways to the acquisition of task-related resources, for instance information or expertise, expressive ties such as friendship have been associated more strongly with psychological resources, such as social support (Balkundi & Harrison, 2006; Lincoln & Miller, 1979). Since they have been shown to be theoretically distinct and to partly fulfil different functions in the workplace (e.g., Baldwin, Bedell, & Johnson, 1997; Fang et al., 2015), the two types of ties might be a source of variation for the network-performance relationship in knowledge-intensive contexts.

Finally, following Hülsheger, Anderson, and Salgado (2009), we take into account the type of performance measurement as a potential moderator, and differentiate between subjective performance ratings and objective criteria. Prior meta-analyses have shown that subjective and objective criteria measure different aspects of performance and cannot be used interchangeably (Bommer, Johnson, Rich, Podsakoff, & Kenzie, 1995; Rich, Bommer, MacKenzie, Podsakoff, & Johnson, 1999). In line with this, it has even been explicitly recommended that "when reviews of the literature are conducted, results should be grouped by the type of performance criteria" (Heneman, 1986: 820). Following this recommendation, we examine whether the type of performance measurement systematically influences the network-performance relationship at the levels of individuals and groups.

Method

Literature Search and Coding Procedure

To identify studies for this meta-analysis, we searched the following databases for keywords such as social network, knowledge sharing, innovation, creativity, (virtual) team, group, or project: ABI/inform, EBSCO, EconBiz, Emerald, JSTOR, and Science Direct. Moreover, we reviewed the reference lists of the collected articles and of previous reviews and meta-analyses (e.g., Balkundi & Harrison, 2006; Fang et al., 2015; Payne et al., 2011) for additional studies. The studies we reviewed were not limited to a particular timespan. To control for publication bias, we included unpublished dissertations and conference papers. We searched Dissertation Abstracts, SSRN, as well as the conference programs of relevant conferences such as the Academy of Management Annual Meeting. The search was finalized in early 2016. For inclusion in our meta-analysis, a study had to report an effect size on the relationship between one of the network characteristics under investigation and performance either at the individual or at the group level. Concerning performance, we followed Fang et al. (2015) and included studies reporting job performance (i.e., success in completing work-related tasks and responsibilities) using peer and supervisor ratings or objective measures such as patent counts. Finally, studies had to examine knowledge-intensive work in the context of academia, consulting, engineering, research and development (e.g., new product development), or creative industries (e.g., movie production). This search resulted in a database of 102 studies.

We coded all effect sizes with respect to the level of theorizing (individual or group), the network characteristics under investigation (direct connectedness, global connectedness, bridging of structural holes, boundary spanning, and tie strength), the network measurement (survey vs. archival data), tie content (instrumental vs. expressive) as well as performance criteria (subjective vs. objective). The coding process revealed that studies used a variety of different measures to capture the five network characteristics. The different measures along with the frequency of their usage are displayed in Table 1.

--- Insert Table 1 about here ---

One author coded the information from all studies. To assess the reliability of the coding process the other author independently coded a subsample (one third) of randomly selected studies (for a similar approach see Heugens & Lander, 2009). The inter-rater reliability based on Cohen's Kappa was 0.92 indicating a high level of agreement (Landis & Koch, 1977). All coding disagreements were unanimously resolved through discussion. We allowed articles that report effect sizes on independent samples (e.g., Cross & Cummings, 2004; Tsai, 2001) to contribute multiple coefficients to our analyses. By contrast, if studies reported multiple effect sizes for a given relationship from a single sample (e.g., Collins & Clark, 2003; Ruef, 2002), we computed composite correlations based on the procedure outlined by Hunter and Schmidt (2004). This way, we ensure that stochastic dependencies among effect sizes do not bias our results. In total, this process yielded 209 effect sizes from 109 independent samples described in 102 studies.

Meta-Analytic Methods

We conducted Hunter and Schmidt (2004) random effects meta-analysis and first calculated weighted mean correlations by correcting the observed correlations for sampling error, using the studies' sample sizes as weights. To further correct for measurement error in the network and performance variables, we used artifact distributions (Hunter & Schmidt, 2004) because reliability estimates were not available for all of the studies in our sample. Based on

Cronbach's alpha coefficients contained in the studies that did report reliabilities, we created separate reliability distributions for all variables included in this meta-analysis. In other words, using the available alpha coefficients for each variable, we created one reliability distribution for every network variable, the performance variable, as well as all variables distinguished in the moderator analyses. Reliability distributions were created separately for the two levels. We used these distributions to correct the appropriate variables for unreliability. To avoid overcorrection of measurement errors, we did not adjust objective performance indicators, such as the number of patents or product innovations. We report sample-size weighted uncorrected ($\bar{r}$) and corrected ($\bar{\rho}$) correlations and their standard deviations. Following prior meta-analyses (e.g., Jiao, Richards, & Hackett, 2013; Subramony, 2009) we test the precision and reliability of the mean corrected correlation by calculating the 95% confidence interval. Confidence intervals can be used as a significance test. If a 95% confidence interval does not include zero, we can assume significance of the mean corrected correlation at the level of $\alpha = 0.05$. Moreover, we calculate 80% credibility intervals, which convey information on the variability in the distribution of the average correlation and as such constitute a test of heterogeneity (Hunter & Schmidt, 2004; Whitener, 1990). If a credibility interval is wide and/or includes zero, this suggests the existence of potential moderators for a given relationship. As an additional indicator for the presence of moderators, we calculate the Q-statistic (Hunter & Schmidt, 2004). A significant Q-statistic indicates a lack of homogeneity and thus the presence of moderators. Finally, we perform z-tests (Feingold, 1992) to compare the relative differences in the magnitude of the network-performance relationship at the individual and the group level (for a similar approach see Carney, Gedajlovic, Heugens, Van Essen, & Van Oosterhout, 2011; van Wijk et al., 2008). A significant z-value indicates cross-level differences in magnitude of the corrected correlations.

Results

Following the meta-analytic procedures described above, we first present the results of the individual-level and group-level analyses for the different network characteristics. After that, we investigate cross-level differences in the magnitude of the network-performance relationship and test for proportional homology. Finally, we discuss whether or not our findings are homogenous across studies and explore potential moderator effects.

Meta-Analytic Results for the Individual and Group Level

Table 2 shows the results for the meta-analyses at the levels of individuals and groups. The results reveal that all but one of the tested relationships are significant in the predicted direction as indicated by the 95% confidence intervals excluding zero. Mean corrected correlations range between $\bar{\rho}$ = .10 and $\bar{\rho}$ = .30 indicating small to moderate relationships according to Cohen's (1988) rule of thumb. We find a positive influence of direct connectedness on job performance for individuals ($\bar{\rho}$ = .30, k = 45) and groups ($\bar{\rho}$ = .22, k = 22), providing full support for Hypothesis 1. Concerning the global connectedness-performance relationship, our meta-analysis results in a significant positive mean corrected correlation at the individual level ($\bar{\rho}$ = .13, k = 8) but not at the group level ($\bar{\rho}$ = .13, k = 4). Thus, Hypothesis 2 is only partly supported; opposed to individuals, groups do not seem to benefit from high levels of global connectedness. In line with Hypothesis 3, the findings suggest that bridging structural holes is positively related to individual ($\bar{\rho}$ = .20, k = 48) and group ($\bar{\rho}$ = .26 k = 11) job performance. Similarly, with respect to boundary spanning, we find that individuals ($\bar{\rho}$ = .10, k = 26) and groups ($\bar{\rho}$ = .16, k = 9) benefit from ties crossing pre-defined boundaries. These results support Hypothesis 4 and, in conjunction with the findings on structural holes, highlight the overall benefits accruing from network brokerage in knowledge-intensive contexts. Finally, we find positive mean corrected correlations for the impact of tie strength on performance at the level of individuals ($\bar{\rho}$ = .22, k = 28) and groups ($\bar{\rho}$ = .30, k = 8), providing full support for Hypothesis 5.

--- Insert Table 2 about here ---

As suggested by Geyskens, Krishnan, Steenkamp, and Cunha (2009) we conduct sensitivity analyses to ensure that outliers do not bias our results. Particularly, the sample size of an individual-level study by Lee (2010, N = 116,468) exceeds the sample sizes of the remaining studies synthesized to test Hypotheses 1, 3, and 4 by a great deal. Consequently, we performed all meta-analyses with and without this study. We find that without Lee (2010) the mean corrected correlation for the direct connectedness-performance relationship increases to $\bar{\rho}$ = .36 (95% CI [0.27, 0.44]), for structural holes-performance it slightly decreases to $\bar{\rho}$ = .16 (95% CI [0.11, 0.22]) and for boundary spanning-performance it remains stable at $\bar{\rho}$ = .10 (95% CI [0.07, 0.14]).

Testing Proportional Homology

The above results demonstrate that with respect to its direction (i.e., positive or negative) the network-performance relationship is not moderated by the level of theorizing and thus generalizable across levels. Next, we address whether the influence of networks on performance is (consistently) stronger at the individual level or at the group level. To examine the cross-level differences in the magnitude of the mean corrected correlations for individuals and groups we draw on the result of the z-tests displayed in the last column of Table 2. We find significant differences across levels for three of the five network characteristics. Concerning the direct connectedness-performance relationship the results show that the mean corrected correlation is larger at the individual level. In other words, a high number of direct ties are more beneficial for individual as opposed to group job performance. Conversely, for structural holes and boundary spanning the mean corrected correlations are larger at the group level than at the individual level. Groups reap larger performance benefits from brokerage than individuals. The cross-level differences for global connectedness and tie strength are not significant. Since we find no consistent pattern with respect to differences in the magnitude across the five network characteristics, the network-performance relationship is not characterized by proportional homology as defined by (Chen et al., 2005a). Nevertheless, the results highlight the moderating impact of the level of theorizing on the magnitude of the network-performance relationship.

Test of Additional Moderating Effects

While the 80% credibility intervals for the statistically significant relationships presented in Table 2 do not include zero, some of them are very wide, indicating heterogeneity across studies. Moreover, the Q-statistic is significant for most of the relationships, providing further evidence that moderators may account for significant variability in the study outcomes. Thus, we proceeded by examining whether the network measurement, tie content, and performance criteria function as moderators. We expect an improvement in the homogeneity indicators (i.e., a smaller credibility and non-significant Q-values) if these variables are meaningful moderators for the different relationships. The results of our moderator analysis are displayed in Table 3.

--- Insert Table 3 about here ---

Comparing studies that rely on survey data to those investigating archival data, our results show some variation in the magnitude of the different relationships. Particularly, studies relying on archival data exhibit larger mean corrected correlations for direct and global connectedness as well as structural holes. Most strikingly, the structural holes-performance relationship becomes insignificant for survey-data studies at the group level. In sum, however, homogeneity indicators improve only marginally. We further sub-categorize studies using survey data according to tie content and performance criteria under investigation. We do not sub-categorize studies drawing on archival data as they all investigate instrumental ties and draw on objective performance criteria. Focusing on the distinction between instrumental and expressive networks shows that only very few group-level studies take into account expressive ties. Excluding them from the analyses does not change our findings. We also find that, particularly for the global connectedness-performance relationship at the individual level, tie content functions as a moderator. Yet, due to the small number of effect sizes these findings should be interpreted with caution. Again, homogeneity indicators do not improve noticeably. Finally, we find that performance criteria do not moderate the network-performance relationship, except for noticeably larger effect sizes for objective performance with respect to the tie strength-performance relationship at both levels. Homogeneity indicators improve only marginally. In sum, these results reveal that the moderators under investigation only sporadically account for the significant variation among the different network-performance relationships. Moreover, moderating effects are neither consistent across network characteristics nor across levels. We will proceed with discussing the implications of our findings.

Discussion

Implications for Research

The purpose of our study is to test the generalizability of the network-performance relationship across the levels of individuals and groups and to derive conclusions on cross-level differences in magnitude. While past studies have assumed that the influence of networks on performance is homologous (e.g., Moliterno & Mahony, 2011), our results offer a more fine-grained picture. Our meta-analytic findings highlight, first, that individuals and groups profit from a high number of direct connections and individuals benefit from indirect connections.

Aggregating the results of several single-sample studies, it becomes clear that the advantages of having a central network position outweigh its disadvantages, such as time constraints and coordination costs, at both levels. Concerning global connectedness, our findings indicate that opposed to individual job performance, group performance does not depend on indirect ties offering access to the overall network. Instead, only network characteristics related to direct ties (i.e., direct connectedness, brokerage, and tie strength) matter for success at the group level. However, the latter finding should be interpreted with caution because the number of meta-analyzed studies investigating global connectedness at both levels was considerably smaller than the number of studies taken into account with respect to the remaining network characteristics. Second, we show that individual and group performance benefits from bridging structural holes and spanning boundaries rather than embeddedness in dense networks. These findings support the notion that in knowledge-intensive contexts the ”bridging” view of social capital that builds on the concept of brokerage (Burt, 2005) provides a better explanation for performance than the traditionally contrasted ”bonding” view focusing on network closure (Coleman, 1988). Finally, we show that the strength of a tie is positively related to job performance of individuals and groups in the context of knowledge-intensive work. In sum, these results reveal that – with the exception of global connectedness – the different relationships are consistently significant across levels, demonstrating metaphoric homology (Chen et al., 2005a).

Regarding cross-level differences in magnitude, we challenge the homology assumption by showing that the level of theorizing moderates the network-performance relationship. Mean corrected correlations differ for individuals and groups for all network characteristics except global connectedness and tie strength. Yet, opposing the notion of proportional homology (Chen et al., 2005a), the differences in magnitude are not consistent across the different network characteristics. The results demonstrate that direct connectedness is more beneficial for individuals than for groups. Despite the possibility for group members to divide tie creating activities and thus share the burden of time constraints and distractions, it seems that individuals are better able to make use of a high number of direct contacts. Possibly, group-internal coordination requirements cause the lower magnitude of the direct connectedness-performance relationship at the group level. These requirements might make it more difficult for groups to efficiently handle large amounts of information and knowledge received through the sum of their members' direct ties and integrate them into their already complex work. With respect to structural holes and boundary spanning, our findings highlight that the network-performance relationship is stronger at the group level than at the individual level. A possible explanation for this finding could be that, concerning these more complex network characteristics which extend beyond the sheer number of ties, groups benefit from specialization advantages in spite of existing coordination requirements. In other words, they may succeed to strategically distribute brokerage activities among their members. As suggested above, it is also likely that the burdens resulting from normative demands and different role expectations ascribed to brokerage (Krackhardt, 1999) are less perceptible at the group level if every group member specializes and strategically creates ties on behalf of the group.

Despite having added little to explain heterogeneity across studies, our moderator analyses offer implications for research on the network-performance relationship. Particularly, the differences in magnitude between survey and archival data indicate that there are variations between "social networks" captured by using survey data and "membership networks" derived from archival data (Breiger, 1974). The larger correlations for studies based on archival data indicate that, compared to surveys, databases may be a less biased way to collect network data.

The finding may also be an indication for a common method bias resulting from the use of the same data source (i.e., patents or publications) to derive network and performance variables. Either way, scholars should be aware of how the type of network measurement as well as other aspects of the study design, such as the choice of performance indicators, may influence their results.

All in all, our meta-analysis and cross-level comparison contribute to a refinement of the implicit notion that the network-performance relationship is generalizable across levels. In the past, scholars have repeatedly referred to studies conducted at one level to draw conclusions on the network-performance relationship at another level (e.g., Lechner et al., 2010; Zaheer & Soda, 2009) without discussing the validity of such cross-level inferences. Our results highlight to what extent this practice is appropriate and draw attention to important boundary conditions concerning differences in the magnitude of the relationship across levels. In addition, the few network scholars explicitly reflecting on the notion of multilevel homology have typically been vague about the specific type of homology (e.g., Moliterno & Mahony, 2011; Payne et al., 2011). By demonstrating that the network-performance relationship is not characterized by proportional homology, because differences in magnitude are not consistent across the five network characteristics, our study suggests that a multilevel homology theory of networks cannot be independent of the specific network characteristic under investigation. Instead, it needs to take into account the different benefits and costs associated with each network characteristic when investigating its impact on performance at different levels.

Practical Implications

Our findings have practical implications for managers and human resource professionals who aim at assisting individuals and groups to create ties that are beneficial for job performance thereby ultimately generating a competitive advantage for the entire organization (Collins & Clark, 2003). First, we raise awareness for the distinction between individual-level and group-level networks in knowledge-intensive contexts. Practitioner-oriented literature largely concentrates on the individual, making recommendations on how individual networks can be optimized (Hollenbeck & Jamieson, 2015; Kaše, King, & Minbaeva, 2013), but neglects the perspective of the group. Our study demonstrates that for inter-group networks, the whole is different from the sum of its parts, as specialization advantages and coordination requirements influence how groups can make use of their members' aggregated ties. HR managers can draw upon this finding and develop team building practices that include a focus on the effective creation of inter-group ties. They may point out that – according to our findings – specialization advantages may be particularly beneficial with respect to brokerage, and based on this, encourage group members to coordinate their tie-creating activities in this respect. A first step to do this is mapping the group members' existing ties in order to assess their overlap, and consequently identify and address network inefficiencies. Given the rising importance of team work and of managing entire groups as compared to managing the individual, especially in knowledge-intensive contexts, this focus on the group and its external networks can help HR practitioners modify intra-organizational networks for performance in a targeted way.

Second, while HR managers have the ideal position in an organization to influence network development (Carboni & Ehrlich, 2013), they have so far been confronted with fractional and heterogeneous results concerning the network-performance relationship. Our study provides them with an overview and a clarification of the network characteristics that are actually beneficial for the performance of individuals and groups. Thus, when assessing the networks in their own organization (by use of survey or archival data), they have a reference of which characteristics to measure at the level of individuals and groups. Based on their assessment, they can then select network configuration-changing HR practices such as work design, incentives, and training as discussed by Kaše, Paauwe, and Zupan (2009) to support the creation of networks which exhibit these beneficial characteristics. As an example, cross-functional training can facilitate the creation of boundary-spanning ties among individuals and groups. Hollenbeck and Jamieson (2015) also suggest that key figures on different network characteristics can be incorporated in performance appraisals to give employees an opportunity to reflect on and if necessary adapt their network embeddedness. In this respect, HR managers should be aware – and pass on this awareness – that tie creation is not the only means to adapt a network. Instead, modifications may include the reinforcement of existing ties to increase tie strength, for instance by providing additional opportunities for interaction. Likewise, the termination of ties may be considered if at the group level a lot of overlap exists among the individual members' ties. The latter can be fostered by HR activities such as redefining job descriptions and responsibilities for the individual. Of course, concerning tie termination, HR managers and the affected individuals and groups need to weigh the individuals' good against the good of the entire group.

Limitations and Future Research

Some limitations to our study offer opportunities for future research. First, our findings are specific to knowledge-intensive contexts where networks are of particular importance for successful task completion. An interesting extension of our research would be to investigate whether cross-level differences of the network-performance relationship for individuals and groups vary depending on different degrees of task interdependence and complexity. Second, the results of our moderator analysis call for future research in at least two directions. In general, they demonstrate a lack of studies for some of the subgroups we created, for instance group-level research investigating the performance benefits of expressive ties. More importantly, they suggest that the network-performance relationship might be more complex than can be captured by the variables under investigation. None of the considered moderators affect all network characteristics or both levels simultaneously, thus indicating the necessity to introduce different moderators for different network characteristics and at different levels which is outside the scope of our study. Finally, future research is needed to analyze the determinants of the differences in magnitude that we have discovered across the levels of individuals and groups. Cross-level influences may play an important role and their examination can be seen as another step towards the development of a multilevel theory of social networks. For instance, studies might look into the importance of individual-level factors and interpersonal processes for groups' ability to make use of their specialization advantages. As our findings on cross-level differences in magnitude imply, it might not be the complexity of network characteristics that increases the requirements for team-internal coordination, but the number of direct ties held by each group member. Future research might also analyze how the distribution of networking activities among members of a group influences an individual group member's job performance, taking into account his or her overall network embeddedness. A better understanding of such multilevel influences would not only be of theoretical interest and resolve some of the moderator issues discussed above, but it would also benefit practitioners aiming to manage individuals' and groups' network embeddedness in order to gain competitive advantages for their organization.

Notes

[1] It seems that while norms and trust are assumed to play an important role at the individual level, they are less salient concepts for the investigation of networks between groups. They do, however, often attract the attention of scholars analyzing within-group networks (Balkundi & Harrison, 2006; Oh et al., 2004), which are outside the scope of this study. Yet, this observation highlights an important area for future group-level network research.

[2] As highlighted by Levin et al. (2015) scholars sometimes conflate relational and structural approaches to networks when investigating tie strength. They build on Granovetter's (1973) "strength of weak ties" theory to argue that weak ties allow access to new and diverse information when, in fact, this is rather a function of the bridging effect of a tie that often correlates with weakness (Moran, 2005; Podolny, 2001). As summarized by Podolny (2001: 34): "controlling for the extent to which a tie serves as a bridge to distinctive sources of information, stronger ties are actually more beneficial than weak ties since they allow a greater volume of resources to move between actors".

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Table 1
List of Measures Employed in the Literature to Capture the Five Network Characteristics

Network characteristic	Measure (Number of effect sizes)
Direct connectedness	Degree centrality (40)
	Out-degree centrality (21)
	In-degree centrality (8)
Global connectedness	Closeness centrality (5)
	Eigenvector centrality (4)
	Bonacich power centrality (2)
	Coreness (1)
	Stephenson and Zelen centrality (1)
Structural holes	Constraint*/ inverted constraint (23)
	Betweenness centrality (19)
	Ego-density*/ inverted ego-density (16)
	Efficiency (8)
	Brokerage measure (2)
	Effective network size (1)
	Ego-network closure* (1)
	Local clustering* (1)
	Number of components (1)
Boundary spanning	Functional boundaries (20)
	Knowledge-based boundaries (7)
	Aggregated categories (4)
	Multi-item constructs (3)
	Geographical boundaries (2)
	Hierarchical boundaries (2)
	Demographic boundaries (1)
Strength	Frequency (19)
	Aggregated categories (11)
	Emotional closeness (5)
	Duration (1)
	Importance (1)
	Trust (1)

Note: The overall number of effect sizes reported in brackets can exceed the number of effect sizes reported in the meta-analytic results because some studies use multiple measures to capture a specific network characteristic and we computed composite correlations as described in the manuscript. *For these measures, low values indicate structural holes. Effect sizes based on these measures were inverted before aggregating them with the remaining measures.

Table 2
Meta-Analytic Results for the Network-Performance Relationship at the Levels of Individuals and Groups

Analysis	k	N	$\bar{r}$	SD_r	$\bar{\rho}$	SD_ρ	80% CV		95% CI		Q	z
Direct connectedness – performance												
Individual level	45	276504	0.27	0.21	0.30	0.22	0.02	0.58	0.23	0.37	21146*	5.58*
Group level	22	4584	0.20	0.14	0.22	0.12	0.07	0.38	0.16	0.29	113*	
Global connectedness – performance												
Individual level	8	153752	0.11	0.07	0.13	0.22	0.04	0.22	0.07	0.18	812*	0
Group level	4	155	0.11	0.24	0.13	0.18	-0.11	0.36	-0.13	0.39	10*	
Structural holes – performance												
Individual level	48	277102	0.18	0.14	0.20	0.15	0.01	0.38	0.15	0.24	7987*	3.01*
Group level	11	2470	0.23	0.09	0.26	0.07	0.17	0.34	0.20	0.32	21*	
Boundary spanning – performance												
Individual level	26	195601	0.10	0.05	0.10	0.05	0.04	0.17	0.08	0.13	598*	2.43*
Group level	9	1756	0.13	0.09	0.16	0.06	0.09	0.24	0.09	0.23	15	
Tie strength – performance												
Individual level	28	72750	0.19	0.05	0.22	0.05	0.16	0.28	0.20	0.24	194*	1.88
Group level	8	590	0.27	0.17	0.30	0.13	0.13	0.46	0.17	0.42	17*	

Note: k = number of effect sizes; N = combined sample size; $\bar{r}$ = uncorrected weighted mean correlation; SD_r = standard deviation of $\bar{r}$; $\bar{\rho}$ = mean true score correlation corrected for unreliability in both variables; SD_ρ = standard deviation of ρ; CV = credibility interval; CI = confidence interval; Q = test for homogeneity in the true correlation across studies; z = result of the significance test on the difference in $\bar{\rho}$ between two groups; *p < .05.

Table 3
Moderator-Analysis

Analysis	k	N	$\bar{r}$	SD_r	$\bar{\rho}$	SD_ρ	80% CV		95% CI		Q	z
Direct connectedness-performance at the individual level												
Archival data	18	272631	0.27	0.21	0.30	0.22	0.02	0.57	0.19	0.40	20921*	4.39*
Survey data	27	3873	0.20	0.20	0.23	0.19	-0.02	0.48	0.14	0.32	161*	
Instrumental ties	23	3248	0.19	0.20	0.22	0.20	-0.04	0.47	0.12	0.31	170*	2.49*
Expressive ties	5	664	0.27	0.17	0.32	0.16	0.11	0.52	0.14	0.49	22*	
Objective performance	4	644	0.20	0.19	0.22	0.18	-0.01	0.45	0.02	0.42	24*	0.28
Subjective performance	23	3229	0.20	0.20	0.23	0.20	-0.02	0.49	0.14	0.33	170*	
Direct connectedness-performance at the group level												
Archival data	7	3476	0.21	0.11	0.23	0.11	0.08	0.37	0.12	0.34	51*	1.14
Survey data	15	1000	0.16	0.20	0.19	0.17	-0.03	0.40	0.07	0.30	55*	
Instrumental ties	15	1000	0.16	0.20	0.19	0.17	-0.03	0.40	0.07	0.30	55*	-
Expressive ties	0	-	-	-	-	-	-	-	-	-	-	
Objective performance	5	229	0.22	0.20	0.24	0.14	0.06	0.43	0.05	0.43	10	0.98
Subjective performance	10	771	0.14	0.19	0.17	0.16	-0.04	0.38	0.03	0.31	43*	
Global connectedness-performance at the individual level												
Archival data	5	91326	0.14	0.08	0.15	0.09	0.05	0.26	0.08	0.23	564*	12.88*
Survey data	3	62426	0.08	0.03	0.09	0.30	0.05	0.13	0.05	0.13	90*	
Instrumental ties	3	62426	0.16	0.02	0.19	0.27	0.16	0.22	0.16	0.22	71*	39.08*
Expressive ties	2	62329	-0.03	0.02	-0.03	0.35	-0.06	0.00	-0.07	0.01	52*	
Objective performance	0	-	-	-	-	-	-	-	-	-	-	-
Subjective performance	3	62426	0.08	0.03	0.09	0.30	0.05	0.13	0.05	0.13	90*	
Global connectedness-performance at the group level												
Archival data	3	128	0.10	0.26	0.11	0.22	-0.18	0.39	-0.22	0.43	10*	-
Survey data	1	-	-	-	-	-	-	-	-	-	-	
Instrumental ties	1	-	-	-	-	-	-	-	-	-	-	-
Expressive ties	0	-	-	-	-	-	-	-	-	-	-	
Objective performance	0	-	-	-	-	-	-	-	-	-	-	-
Subjective performance	1	-	-	-	-	-	-	-	-	-	-	
Structural holes-performance at the individual level												
Archival data	16	271228	0.19	0.14	0.19	0.14	0.01	0.38	0.12	0.27	7822*	5.42*
Survey data	32	5874	0.11	0.14	0.12	0.12	-0.03	0.28	0.07	0.18	129*	
Instrumental ties	29	5388	0.11	0.14	0.13	0.13	-0.04	0.30	0.07	0.19	124*	0.58
Expressive ties	3	442	0.09	0.12	0.10	0.09	-0.01	0.21	-0.05	0.25	6	
Objective performance	6	2016	0.09	0.05	0.10	0.00	0.10	0.10	0.06	0.15	5	1.21
Subjective performance	26	3858	0.12	0.17	0.13	0.16	-0.07	0.33	0.06	0.20	122*	

Table 3

Moderator-Analysis (continued)

Analysis	k	N	$\bar{r}$	SD_r	$\bar{\rho}$	SD_ρ	80% CV		95% CI		Q	z
Structural holes-performance at the group level												
Archival data	6	2220	0.25	0.05	0.27	0.00	0.27	0.27	0.22	0.31	6	2.47*
Survey data	5	250	0.09	0.20	0.10	0.15	-0.09	0.30	-0.10	0.31	10	
Instrumental ties	4	235	0.07	0.19	0.08	0.16	-0.12	0.28	-0.14	0.31	9*	-
Expressive ties	1	-	-	-	-	-	-	-	-	-	-	
Objective performance	1	-	-	-	-	-	-	-	-	-	-	-
Subjective performance	4	235	0.07	0.19	0.08	0.16	-0.12	0.28	-0.14	0.31	9*	
Boundary spanning-performance at the individual level												
Archival data	6	190847	0.09	0.04	0.09	0.03	0.06	0.13	0.06	0.13	394*	10.74*
Survey data	20	4754	0.22	0.14	0.25	0.11	0.10	0.39	0.18	0.31	112*	
Instrumental ties	20	4754	0.23	0.14	0.25	0.11	0.11	0.39	0.18	0.31	110*	-
Expressive ties	1	-	-	-	-	-	-	-	-	-	-	
Objective performance	5	2585	0.19	0.11	0.21	0.11	0.07	0.35	0.10	0.32	40*	2.07*
Subjective performance	16	2899	0.24	0.15	0.26	0.14	0.09	0.44	0.18	0.34	77*	
Boundary spanning-performance at the group level												
Archival data	1	-	-	-	-	-	-	-	-	-	-	-
Survey data	8	528	0.19	0.15	0.23	0.10	0.10	0.35	0.10	0.35	12	
Instrumental ties	7	468	0.16	0.14	0.20	0.08	0.09	0.30	0.07	0.32	10	-
Expressive ties	1	-	-	-	-	-	-	-	-	-	-	
Objective performance	1	-	-	-	-	-	-	-	-	-	-	-
Subjective performance	7	455	0.16	0.15	0.20	0.09	0.08	0.32	0.07	0.33	11	
Tie strength-performance at the individual level												
Archival data	9	64065	0.19	0.04	0.22	0.04	0.17	0.27	0.19	0.25	92*	0.21
Survey data	19	8685	0.18	0.10	0.22	0.10	0.09	0.35	0.16	0.27	101*	
Instrumental ties	19	8685	0.18	0.10	0.22	0.10	0.09	0.35	0.16	0.27	101*	-
Expressive ties	0	-	-	-	-	-	-	-	-	-	-	
Objective performance	5	6868	0.21	0.08	0.24	0.08	0.14	0.35	0.16	0.33	49*	7.71*
Subjective performance	15	2547	0.06	0.10	0.07	0.07	-0.03	0.16	0.01	0.13	28*	
Tie strength-performance at the group level												
Archival data	0	-	-	-	-	-	-	-	-	-	-	-
Survey data	8	590	0.27	0.17	0.30	0.13	0.13	0.46	0.17	0.42	17*	
Instrumental ties	7	575	0.27	0.17	0.30	0.14	0.12	0.48	0.16	0.44	17*	-
Expressive ties	1	-	-	-	-	-	-	-	-	-	-	
Objective performance	4	237	0.38	0.05	0.40	0.00	0.40	0.40	0.35	0.45	1	2.34*
Subjective performance	4	353	0.20	0.18	0.22	0.16	0.02	0.42	0.03	0.42	12*	

Note: k = number of effect sizes; N = combined sample size; $\bar{r}$ = uncorrected weighted mean correlation; SD_r = standard deviation of $\bar{r}$; $\bar{\rho}$ = mean true score correlation corrected for unreliability in both variables; SD_ρ = standard deviation of ρ; CV = credibility interval; CI = confidence interval; Q = test for homogeneity in the true correlation across studies; z = result of the significance test on the difference in $\bar{\rho}$ between two groups; in single cases, the sum of effect sizes can exceed the overall k reported in Table 2 due to (dis-) aggregation of measures (e.g., studies capturing both, instrumental and expressive ties). *p < .05.

Appendix

Studies Included in the Meta-Analysis

Study	Level of theorizing	Direct connectedness	Global connectedness	Structural holes	Boundary spanning	Strength	Data source	Network type	Performan-ce measure
Abbasi et al. (2012)	individual	x		x			archival	instrumental	objective
Abbasi et al. (2014)	individual	x		x		x	archival	instrumental	objective
Ancona & Caldwell (1992)	group					x	survey	instrumental	subjective
Anderson (2006)	individual			x			survey	instrumental	subjective
Anderson (2008)	individual	x		x		x	survey	instrumental	subjective
Baer (2010)	individual	x			x	x	survey	instrumental	subjective
Baldwin et al. (1997)	individual		x				survey	expressive, instrumental	subjective
Beaudry & Allaoui (2012)	individual			x			archival	instrumental	objective
Beaudry & Kananian (2013)	individual			x			archival	instrumental	objective
Bertolotti et al. (2015)	group	x					survey	instrumental	objective
Brands, Kilduff (2014)	individual	x		x			survey	expressive	subjective
Brion et al. (2012)	group				x		survey	instrumental	subjective
Burt (2000)	individual	x		x			survey	instrumental	subjective
Burt (2004)	individual			x			survey	instrumental	subjective
Burt (2007)	individual			x			survey	instrumental	subjective
Burton (2007)	individual			x			survey	instrumental	subjective
Cattani & Ferriani (2008)	individual		x	x			archival	instrumental	objective
Chen & Gable (2013)	individual	x			x		survey	instrumental	subjective
Chen & Liu (2012)	individual	x			x		archival	instrumental	objective
Chiu (2013)	individual	x					archival	instrumental	objective
Chung & Jackson (2013)	group	x				x	survey	instrumental	objective
Clarke Garcia (2014)	individual				x		survey	instrumental	subjective
Collins & Clark (2003)	group	x			x	x	survey	instrumental	objective
Cross & Cummings (2004)	individual			x	x		survey	instrumental	subjective
Cross & Sproull (2004)	individual				x	x	survey	instrumental	subjective
Cummings (2004)	group					x	survey	instrumental	subjective
Cummings & Haas (2012)	group	x					survey	instrumental	subjective
Ding et al. (2010)	individual	x					archival	instrumental	objective
Faraj & Yan (2009)	group				x		survey	instrumental	subjective
Fleming et al. (2007)	individual	x		x		x	archival	instrumental	objective
Fleming & Waguespack (2007)	individual	x		x	x		archival	instrumental	subjective
Funk (2014)	individual	x		x			archival	instrumental	objective
Gargiulo & Benassi (2000)	individual			x			survey	instrumental	objective
Gonzalez-Brambila et al. (2013)	individual	x	x	x	x	x	archival	instrumental	objective
Grewal et al. (2006)	group	x	x	x			archival	instrumental	objective
Grosser (2014)	individual			x			survey	instrumental	subjective
Grosser et al. (2016)	individual	x		x	x		survey	instrumental	subjective
Haas (2010)	group				x		survey	instrumental	subjective
Hahn et al. (2013)	individual	x		x			survey	instrumental	subjective
Harhoff et al. (2013)	individual	x		x		x	archival	instrumental	objective
Hemphälä & Magnusson (2012)	individual	x		x			survey	expressive	subjective
Hinds (2008)	group	x					archival	instrumental	objective

Appendix

Studies Included in the Meta-Analysis (continued)

Study	Level of theorizing	Direct connectedness	Global connectedness	Structural holes	Boundary spanning	Strength	Data source	Network type	Performan-ce measure
Ibarra (1993)	individual		x				survey	expressive, instrumental	subjective
Jiang & Chen (2015)	individual	x					survey	expressive, instrumental	objective
Katz (1982)	group				x		survey	instrumental	subjective
Keller (2001)	group					x	survey	instrumental	objective
Kratzer et al. (2008)	group	x					survey	instrumental	subjective
Kratzer et al. (2010)	group	x		x		x	survey	instrumental	subjective
Lechner et al. (2010)	group	x		x		x	survey	instrumental	subjective
Lee (2010)	individual	x		x	x		archival	instrumental	objective
Li et al. (2013)	individual	x	x	x			archival	instrumental	objective
Liao (2011)	individual	x				x	archival	instrumental	objective
Liu (2011)	individual	x		x			archival	instrumental	objective
Liu et al. (2010)	individual			x			archival	instrumental	objective
Liu & Lin (2012)	individual	x		x			archival	instrumental	objective
Llopes (2014)	individual			x	x		survey	instrumental	objective
Lopaciuk-Gonczaryk (2011)	individual	x					survey	expressive	subjective
Maritz (2010)	individual					x	survey	instrumental	objective
Marrone (2004)	individual	x			x		survey	instrumental	subjective
Marrone et al. (2007)	group				x		survey	instrumental	subjective
McFadyen & Cannella (2004)	individual	x				x	archival	instrumental	objective
McFadyen et al. (2009)	individual			x		x	archival	instrumental	objective
Mehra et al. (2001)	individual	x		x			survey	expressive, instrumental	subjective
Mizruchi et al. (2011)	individual	x		x		x	survey	instrumental	subjective
Moran (2005)	individual	x		x		x	survey	instrumental	subjective
Mors (2010)	individual	x		x			survey	instrumental	subjective
Mors & Lynch (2008)	individual	x			x	x	survey	instrumental	subjective
Mote (2005)	group	x	x	x			archival	instrumental	objective
Obstfeld (2005)	individual	x		x			survey	expressive, instrumental	subjective
Oh et al. (2004)	group				x		survey	expressive	subjective
Oldroyd (2007)	individual	x		x			survey	instrumental	subjective
O'Reilly & Roberts (1977)	group	x					survey	instrumental	subjective
Papa (1990)	individual	x		x	x	x	survey	instrumental	objective
Paruchuri (2010)	individual		x		x		archival	instrumental	objective
Peng et al. (2013)	group	x			x		archival	instrumental	objective
Perry-Smith (2006)	individual		x	x	x	x	survey	instrumental	subjective
Perry-Smith & Shalley (2014)	group	x		x	x		survey	instrumental	subjective
Rhee & Ji (2011)	individual	x					survey	instrumental	subjective
Rodan & Galunic (2004)	individual	x		x	x		survey	instrumental	subjective
Rost (2011)	individual			x		x	survey	instrumental	objective
Rotolo & Messeni Petruzzelli (2013)	individual		x		x		archival	instrumental	objective

Appendix

Studies Included in the Meta-Analysis (continued)

Study	Level of theorizing	Direct connectedness	Global connectedness	Structural holes	Boundary spanning	Strength	Data source	Network type	Performance measure
Ruef (2002)	individual				x	x	survey	instrumental	subjective
Sanner et al. (2014)	individual, group	x			x		survey	instrumental	subjective
Soda et al. (2004)	group	x		x			archival	instrumental	objective
Song et al. (2007)	group	x	x	x			survey	instrumental	subjective
Sosa (2011)	individual			x		x	survey	instrumental	subjective
Teigland & Wasko (2003)	individual				x	-	survey	instrumental	subjective
Tortoriello (2015)	individual	x		x	x		survey	instrumental	objective
Tsai (2001)	group	x					survey	instrumental	objective
Tsai & Ghoshal (1998)	group			x		x	survey	expressive	objective
Venkataraman et al. (2014)	individual			x		x	survey	instrumental	subjective
Vernet et al. (2015)	group			x			archival	instrumental	objective
Wang (2015)	individual	x		x		x	survey	instrumental	subjective
Wang (2016)	individual	x				x	archival	instrumental	objective
Wang et al. (2012)	group	x					archival	instrumental	objective
Wisker (2011)	individual	x				x	survey	instrumental	subjective
Wong (2008)	group	x					survey	instrumental	subjective
Xia et al. (2009)	individual					x	survey	instrumental	subjective
Yuan & Gay (2006)	individual				x		survey	expressive, instrumental	subjective
Zaheer & Soda (2009)	group			x	x		archival	instrumental	objective
Zhou et al. (2009)	individual			x		x	survey	instrumental	subjective
Zou & Ingram (2013)	individual	x		x	x		survey	instrumental	subjective