The social network side of individual innovation: A meta-analysis and path-analytic integration

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Abstract
The current study provides a comprehensive analysis and integration of the literature on the social network correlates of individual innovation. Reviewing the extant literature, we cluster existing network measures into five general properties—size, strength, brokerage, closure, and diversity. Using meta-analysis, we estimate the population effect sizes between these network properties and innovation. Results showed that brokerage had the strongest positive relation to innovation, followed by size, diversity, and strength. Closure, by contrast, had a weak, negative association with innovation. In addition, we offer a path-analytic integration of the literature proposing and testing the direct and indirect effects of the five properties on innovation. We suggest that network size and strength impact innovation through a web of relations with the more proximal features of brokerage, closure, and diversity. Our path-analytic integration considers the two dominant perspectives on the effects of social networks—brokerage versus closure—simultaneously allowing us to establish their relative efficacy in predicting innovation. In addition, our model highlights that network strength can have both negative and positive effects (via different direct and indirect pathways) and thus inherently involves a tradeoff. We discuss the implications of these results for future research and practice.
There is widespread scholarly consensus that innovation constitutes a critical competitive advantage and is becoming increasingly important in allowing organizations to survive and thrive (Damanpour & Schneider, 2006; Tellis, Prabhu, & Chandy, 2009). Over the past two decades, scholars and commentators have increasingly emphasized that the relationships individuals cultivate and the positions they occupy in their social networks hold some of the keys to unleashing their innovative potential (e.g., Brass, 1995; Ibarra, 1993; Perry-Smith & Shalley, 2003). Indeed, as evidence is accumulating that neither the production of new ideas nor the execution of these ideas is the domain of the lone genius (e.g., Baer, 2012; Uzzi & Spiro, 2005; Wuchty, Jones, & Uzzi, 2007), there has been burgeoning interest in identifying the features of individuals’ social networks that are most powerful in boosting individual innovation in organizations (Phelps, Heidl, & Wadhwa, 2012).

This growing body of research has focused on a wide array of network characteristics—ranging from relational (e.g., tie strength) and nodal (e.g., functional background) to positional (e.g., betweenness centrality) and structural (e.g., density) features—and has produced an impressive number of empirical findings. Properties that have been featured more prominently in this literature and that have been found to impact individual innovation, include the size of the network (e.g., Baer, 2010; McFadyen & Cannella, 2004), the average strength of the relationships comprising the network (e.g., McFadyen, Semadeni, & Cannella, 2009; Rost, 2011) or, alternatively, the number of weak/strong ties in the network (e.g., Perry-Smith, 2006; Zhou, Shin, Brass, Choi, & Zhang, 2009), the extent to which network contacts are interconnected or, alternatively, the extent to which the network provides opportunities for brokerage (e.g., Burt, 2004; Obstfeld, 2005), a person’s centrality in the network (e.g., Mehra, Kilduff, & Brass, 2001; Perry-Smith, 2006), and the network’s diversity (Baer, 2010; Rodan & Galunic, 2004).

Despite some evidence that the resources (e.g., task advice, strategic information, buy-in, social support; Podolny & Baron, 1997) accessible through social networks play a key role in sparking creative ideas and fueling attempts to subsequently execute and capitalize on these ideas (e.g., Anderson, 2008; Cross & Sproull, 2004), a number of important issues regarding the link between social networks and innovation remain unresolved. First, the proliferation of properties that are being studied, the different ways in which these features have been operationalized across studies, and the fact that work in this area is fragmented across multiple academic disciplines (e.g., management, sociology, political science) represents a challenge for the literature and, as a result, it is not clear which network properties impact innovation more than others. Thus, there is a need for these literatures to be summarized in an integrative fashion allowing for the comparison of the effects of various network features. A meta-analysis allows us to identify true population effect sizes (Hunter & Schmidt, 2004) and compare the various effects with one another to determine which forces are most potent.

Second, along with the variety of variables that have been studied, there are also conflicting theoretical lenses through which the link between networks and innovation has been examined. Specifically, there is a longstanding debate about the relative potency for innovation of network structures that offer opportunities for brokerage between otherwise disconnected parts of the network (e.g., Burt, 1992) and
closed structures, in which most people in the network are connected to one another (e.g., Coleman, 1988). Although many scholars assume that closure and brokerage are opposite ends of the same continuum, both are associated with distinct theoretical arguments and distinct operationalizations. In the present study, we consider both perspectives simultaneously contrasting their relative efficacy in predicting innovation thereby highlighting the unique role each plays.

Third, few if any attempts to examine the linkages between individuals’ social networks and innovation have considered potential mediating mechanisms. However, there is good theoretical and empirical evidence to suggest that certain network properties may operate through other elements of the network to exert their influence on innovation. To address this issue, in addition to meta-analytically reviewing the extant literature, we offer a path-analytic integration of this body of work specifying the indirect paths through which certain network features may impact other network characteristics to ultimately shape innovation. Given that estimates of the population effect sizes between the various network features examined here were not readily available, we conducted a second meta-analysis to derive these estimates—the first of its kind according to our knowledge.

Finally, although a number of quantitative reviews of the innovation literature at various levels of analysis have been offered in recent history (e.g., Damanpour, 1991; Hammond, Neff, Farr, Schwall, & Zhao, 2011; Hülsheger, Anderson, & Salgado, 2009), none have considered the role individuals’ social networks may play in affecting individual innovation in organizations. By focusing specifically on the social network correlates of innovation, we hope to provide a complementary perspective to these earlier meta-analytic reviews spurring a more vibrant dialogue between work on social networks and innovation at the individual level of analysis.

Theoretical background and hypotheses

Innovation in organizations

We define innovation as the process of generating new ideas for organizational products, procedures, processes, and service offerings, of testing, developing, and refining these ideas for future use, and of implementing them (e.g., Amabile, 1996; Kanter, 1988; Oldham & Cummings, 1996; van de Ven, 1986; West, 2002). Thus, innovation encompasses creative idea generation and the subsequent execution, adoption, or implementation of these ideas. Although we acknowledge the possibility that factors impacting the inception of a new idea may differ from those that shape whether an idea is subsequently executed (e.g., Axtell et al., 2000; Clegg, Unsworth, Epitropaki, & Parker, 2002; Frese, Teng, & Wijnen, 1999), the literature on the social network correlates of innovation has rarely examined this distinction—neither theoretically nor empirically. Given the state of the literature and the relatively moderate number of studies that have examined the link between innovation and social network properties to begin with, we elected to follow previous meta-analytic efforts on the topic of innovation (e.g., Hülsheger et al., 2009) not distinguishing between idea generation and implementation but instead to focus our attention on examining overall innovation.

Scholars have used a wide array of indicators to measure innovation, ranging from more subjective indicators, such as self/others’ evaluations of a person’s innovation (e.g., Moran, 2005; Rodan & Galunic, 2004) to more objective indicators, such as the number of patents, publications, and forward citations obtained or the prizes awarded for certain innovative achievements (e.g., Fleming, Mingo, & Chen, 2007; Liao, 2011). Although there is some evidence to suggest that predictor–criterion relations may differ systematically across different measurement approaches (e.g., Hammond et al., 2011;
Hülsheger et al., 2009), the strength of our analysis lies in the fact that we combine studies from different fields of inquiry and provide estimates of the strength of the network–innovation relations across different ways of operationalizing innovation.

**Linking network properties directly to innovation**

The extant literature on social networks has considered a wide variety of network properties and ways of operationalizing the various features. In fact, there are numerous measures that seemingly capture the same underlying conceptual idea. For instance, constraint, efficiency, and betweenness centrality all capture the extent to which individuals serve as information conduits between different parts of the network. In addition, there has been a proliferation of operationalizations with some authors creating their own idiosyncratic network indicators. To clarify this picture, we follow previous research (e.g., Burt, 1992) and focus our attention on those concepts and measures that have been most frequently and consistently used in the literature: network size, strength, brokerage, closure, and diversity.

**Network size**, reflecting the number both of direct and secondary ties, acts as a channel to access different sources of information and knowledge (Freeman, 1979; Gabbay & Leenders, 2001; McFadyen & Cannella, 2004). In fact, Anderson (2008) showed that managers with larger networks were able to gather more task-relevant and diverse information. Exposure to more, and more diverse information and perspectives, in turn, may give an individual an edge in identifying existing opportunities for improvement and in having access to the raw material needed to develop fresh ideas for how to exploit them (Campbell, 1960; Mumford & Gustafson, 1988). Consistent with this assertion, McFadyen and Cannella (2004) showed that network size had a positive correlation with a biomedical researcher’s production of impactful (journal-impact weighted) publications. In addition, having more connections enhances the probability of idea implementation by increasing the access an individual has to contacts that may be both willing to engage in and to support a potentially risky venture. Thus, we predict a positive relation between network size and innovation.

**Hypothesis 1.** Network size is positively related to innovation.

**Network strength** reflects the average strength of the relationships comprising a network. The strength of a tie increases as a function of the number and reciprocity of interactions, the affective intensity of a relationship, or the amount of time the relationship has existed (Granovetter, 1973). While tie strength characterizes the quality of the dyadic relationship between two parties, network strength captures the average strength of all relationships in an actor’s network (McFadyen & Cannella, 2004). Therefore, network strength increases as the number of ties in the network that are characterized by frequent interactions, emotional closeness, or long duration increases (Perry-Smith & Shalley, 2003).

Prior examinations of the importance of network strength for innovation have yielded mixed results, with support for its ability to enhance (e.g., Moran, 2005) and restrict (e.g., Perry-Smith, 2006) innovation. According to one line of argumentation, network strength has the potential to boost innovation. While large networks provide enhanced exposure and access to more and different information and knowledge sets, network strength allows for the transfer of these resources such that individuals can comprehend and make use of them (e.g., Kijkuit & van den Ende, 2010). Repeated interactions help parties become more efficient in exchanging complex, noncodified information and allow for the creation of an overlapping knowledge base upon which to generate and interpret ideas (e.g., Bouty, 2000; Hansen, 1999; Reagans & McEvily, 2003). In addition, strength has been suggested and found to be
instrumental in identifying and formulating problems and in providing validation for individuals’ ideas by bolstering their confidence in them, thereby creating the conditions necessary for people to share their ideas persuasively (e.g., Cross & Sproull, 2004). Consistent with this line of reasoning, Fleming et al. (2007) found that repeated collaboration on patents positively correlated with both the novelty (number of new patent subclasses assigned) and future usefulness (number of forward citations) of an inventor’s patents.

In addition, strong networks, particularly those in which strength is derived from members being emotionally close to one another, cultivate trust which creates a nonthreatening arena in which to propose new ideas without the fear of attack, ridicule, or rejection (Krackhardt, 1992; Levin & Cross, 2004). Innovation typically involves taking risks, with individuals exhibiting higher creativity when groups are high in trust (e.g., Clegg et al., 2002), psychological safety (e.g., Baer & Frese, 2003), and social support (e.g., Madjar, 2008). Further, members who interact frequently and over a longer period of time are more likely to feel a sense of obligation to continue the relationship and to reciprocate any past favors or exchanges, thereby motivating assistance in new ventures in order to maintain a balanced relationship (e.g., Granovetter, 1983; Krackhardt, 1992).

Alternatively, network strength may be detrimental to innovation because it decreases the availability of novel, nonredundant information in the network. Weak ties are more likely to connect different groups and to be a source of diverse, nonredundant information (Granovetter, 1973; Powell & Smith-Doerr, 1994). For example, Perry-Smith (2006) observed a positive correlation between the number of weak ties in an employee’s network and supervisor-rated creativity. Similarly, individuals whose connections are predominantly strong are more likely to build redundant knowledge stocks over time by transferring knowledge over repeated interactions (McFadyen & Cannella, 2004). In fact, McFadyen and Cannella (2004) suggested and found that increasing network strength can be detrimental for innovation leading to a reduction in the number of publications.

In strong networks, expectations and exchange rules become ingrained in the relationships, leading individuals to become more cautious about deviating from established practices in order to prevent backlash or rejection from their interaction partners (Krackhardt, 1999). Given that innovation requires deviation from the norm, strong networks may therefore suffocate individuals’ motivation to generate and execute risky ideas (McPherson, Smith-Lovin, & Cook, 2001). This line of reasoning would suggest that network strength may undermine innovation. Based on the previous arguments, we therefore propose competing hypotheses suggesting that network strength may either positively or negatively relate to innovation.

**Hypothesis 2a.** Network strength is positively related to innovation.

**Hypothesis 2b.** Network strength is negatively related to innovation.

Individuals who bridge structural holes (i.e., the gaps in the structure that exist between otherwise disconnected parts of the network) have certain innovation advantages by connecting separate groups and controlling the flow of communication across them. Specifically, brokerage promotes innovation through two mechanisms: obtaining access to nonredundant information and knowledge sets and controlling the presentation and use of resources across contacts (Burt, 2005; Kilduff & Tsai, 2003). First, by connecting separate clusters of individuals, brokers are more likely to be exposed first to new opportunities and to have privileged access to nonredundant information and knowledge sets than if they only had connections within a single, well-connected cluster (Burt, 1992). Having access to unique, nonoverlapping sources of information provides a wider variety of information from which to draw on for
ideas (Harrison & Klein, 2007). Indeed, Mehra et al. (2001) found that connecting otherwise disconnected work colleagues was a positive predictor of innovation.

Second, because brokers bridge otherwise disconnected parts of the network, this affords them a certain amount of control, giving individuals the ability to decide when and with whom to share information across groups (Hargadon & Sutton, 1997). In addition, because brokers reside between disconnected groups, brokerage behavior is less prone to monitoring and control than if groups were able to interact directly (Burt, 2005). In this way, brokers have autonomy to gather and disseminate information between connections, helping them to promote the acceptance and implementation of their new ideas by selectively sharing resources (Burt, 1992; Padgett & Ansell, 1993). Burt (2004) found empirical support for this contention by showing that managers who bridged structural holes not only had ideas that were rated as more valuable, they were also more likely to have their ideas discussed and engaged by senior management and less likely to have them dismissed.

The benefits stemming from occupying a brokerage position, however, may not be enduring. For example, work by Buskens and van de Rijt (2008) showed that in situations in which all actors strive to take advantage of structural holes, the benefits of brokerage quickly evaporate. In addition, serving as a broker may also have the potential to undermine a focal individual’s ability to innovate. For instance, Krackhardt (1999) suggested that bridging a structural hole subjects a broker to competing sets of group norms that may in fact be more constraining than those faced by an actor in a single connected clique. Moreover, given the privileged access to diverse information sets, relaying this information to others with potentially very different ways of seeing the world may result in overload thereby adversely impacting a broker’s ability to capitalize on his or her position (Cross & Parker, 2004). Finally, because a broker’s behavior is less prone to monitoring, brokers could engage in incidental or strategic filtering, distortion, or hoarding of information (Balkundi, Kilduff, Barness, & Michael, 2007; Burt, 1992). Recent research suggests that such behavior, if detected by alters, causes a spiral of distrust and information and knowledge hiding on both sides, ultimately undermining the creativity of the broker (Černe, Nerstad, Dysvik, & Škerlavaj, 2014). To the extent, however, that not all individuals in a network are striving towards structural holes and the focal actor is able to deal with disparate social spheres without taking advantage of his or her position, brokerage should be positively associated with individual innovation.

Hypothesis 3: Brokerage is positively related to innovation.

Closure (i.e., the extent to which the contacts in one’s network are also connected) has the potential to either enhance or reduce an individual’s innovation. Dense networks create trust because overlapping ties make it less likely that people take advantage of each other—violators will be easily identified and will be forced either to amend their behaviors or to leave the network (Coleman, 1990). In addition, network closure, by encouraging information exchange among densely connected people, may enhance innovation by facilitating the creation of a shared base of knowledge upon which constituents can rely to interpret and contribute to a new idea (Milliken, Bartel, & Kurtzberg, 2003; Uzzi, 1997). Thus, when network structures are dense, norms of cooperation are more likely to emerge and be internalized, trust is more likely to be established, and actions can be coordinated more seamlessly—all of which should make it more likely that vital information is shared, that tacit knowledge can be transferred, that conflicting viewpoints can be integrated, and that resources needed to act upon one’s ideas can be more easily secured and mobilized (e.g., Coleman, 1988; Granovetter, 1985; McFadyen et al., 2009; Podolny & Baron, 1997; Reagans & McEvily, 2003). Obstfeld (2005) provided support for this
overall logic. He observed a positive association between network density and individuals’ involvement in the firm’s innovative activities. Through additional interviews, he confirmed that closure allowed for faster coordination in prototyping processes and for the mobilization of support for change.

Alternately, closure may be detrimental to innovation as the frequent, reciprocal interactions that typify dense networks often result in redundant sharing of information and reinforcement of existing group norms and processes. Ties within closed networks tend to connect similar and overlapping social circles, resulting in increased likelihood that information distributed between contacts will be redundant or already known (Granovetter, 1973). Additionally, closed networks create strong social norms, which may inhibit individuals’ willingness to take the risk of suggesting or implementing new ideas (Coleman, 1990). Closure may create social obligations that restrict the ability for individuals to act freely (Mizruchi & Stearns, 2001) — the overlapping ties in dense networks make it easier to detect deviant behavior, improving the likelihood that actors will adhere to established expectations to avoid rejection or sanctions (Coleman, 1988). Individuals in dense networks, therefore, tend to conform, which can deter the sharing or introduction of new ideas (Ahuja, 2000; Obstfeld, 2005). In fact, Fleming et al. (2007) found that network closure exhibited a negative relation with the number of new patent combinations, an indicator of invention novelty. However, patents arising from cohesive networks in their sample were more likely to generate future use, through citations by other inventors, reinforcing that there are positive benefits that may flow from closure. Therefore, we propose competing hypotheses suggesting that closure may either positively or negatively relate to innovation.

**Hypothesis 4a:** Closure is positively related to innovation.

**Hypothesis 4b:** Closure is negatively related to innovation.

The diversity of the network is a potentially invaluable resource for innovation. Diversity typically refers to differences across an individual’s network contacts in terms of both task-oriented (e.g., educational background, tenure) and relations-oriented (e.g., gender, age) features (Jackson, May, & Whitney, 1995; Joshi & Roh, 2009). Diversity is key to innovation because these task- and relations-oriented differences are assumed to reflect more deep-level differences in information and knowledge sets as well as other resources that are necessary for the generation of fresh ideas and for their execution (Adler & Kwon, 2002; Rodan & Galunic, 2004). Specifically, access to heterogeneous sources of information and knowledge may heighten an individual’s sensitivity to existing environmental needs, improving the likelihood of recognizing opportunities for innovation (Perry-Smith & Shalley, 2003; Shane, 2000). Next, being exposed to people from different backgrounds and walks of life enhances the probability not only that individuals may come across ideas that could solve existing problems in other parts of the organization but also that they combine different ideas to generate new solutions altogether (Fleming et al., 2007; Rodan & Galunic, 2004).

Finally, network diversity makes it more likely that individuals know others who can validate their ideas, who can lend their credibility and support, or who can provide other resources (e.g., time, energy) needed to push an idea through to completion. Thus, having access to individuals who are not only fundamentally different from the focal individual but also from each other makes it more likely that individuals are exposed to the variety of perspectives and resources critical to the identification of new opportunities, to the development of new ideas to solve existing problems, and to the implementation of one’s ideas. Consistent with this logic, Perry-Smith (2006) observed a positive correlation between task-oriented diversity and supervisor-rated creativity. In addition, Rodan and Galunic (2004) showed that the
heterogeneity of knowledge accessible through one’s network indeed related positively and significantly to managerial innovation. Based on the previous arguments and results, we therefore predict that network diversity will be positively related to innovation.

**Hypothesis 5:** Network diversity is positively related to innovation.

**Linking network properties directly and indirectly to innovation: A path-analytic model**

In the following, we develop a path-analytic model that specifies the direct and indirect effects through which network size, strength, brokerage, closure, and diversity impact innovation. Our path model complements our previous theoretical analysis of the direct effects on innovation in an important way. Specifically, by modeling both the direct and indirect effects of the five social network properties simultaneously we are able to paint a more comprehensive picture of the effects of social networks on innovation and are able to evaluate the relative strength of each effect. The path model is depicted in Figure 1.

In developing our path model, we conceptualize brokerage and closure as separate forces impacting innovation. Although closure has often been considered as the opposite of brokerage (e.g., Obstfeld, 2005), a close reading of the literature suggests that both properties are associated with distinct theoretical logics and different operationalizations. While the beneficial effects of brokerage on innovation and other outcomes are often attributed to the fact that brokers have privileged access to more fresh ideas and opportunities and can control the flow of information (Burt, 1992, 2004), the effects of closure are typically attributed to the fact that dense network structures promote the development of trust and solidarity and allow for the mobilization of resources and coordinated action (Coleman, 1988; Obstfeld, 2005). In addition, the benefits associated with brokerage tend to be attributed to individuals operating at the intersection between different social spheres whereas the benefits associated with closure seem to stem largely from within the primary social sphere in which the focal actor is operating. Thus, both theoretical logics are not mutually exclusive and can operate simultaneously (Reagans & Zuckerman, 2001). Moreover, each property is typically captured via different measures—brokerage is often operationalized as constraint, efficiency, or centrality (Burt, 1992; Freeman, 1977), while closure is typically captured via network density. Hence, we decided to treat these two network properties as separate entities. This allowed us to not only consider the different ways in which each may shape innovation but also to quantitatively evaluate the relative potency of each property in impacting innovation.
Network size and strength are hypothesized to exhibit direct relations with brokerage—network size is expected to be positively related to brokerage, whereas we expect network strength and brokerage to be negatively linked. The positive association between size and brokerage is rooted both in theoretical and empirical reasons. From a theoretical standpoint, as networks increase in size, the probability increases that individuals from very different backgrounds and with very different interests join the network. Individuals may even cultivate relationships for specific and different purposes (e.g., to obtain advice or to mobilize support; Burt, 1992), resulting in the network becoming more fragmented and allowing individuals to serve as brokers between these otherwise disconnected social worlds (Kilduff & Tsai, 2003). From an empirical standpoint, a number of measures typically used to capture brokerage (e.g., constraint or efficiency) factor network size into the measure itself so that a positive association between the two concepts is likely empirically (e.g., Rodan & Galunic, 2004). Indeed, a study by Fleming and Waguespack (2007) revealed a positive correlation between a measure of network size (the number of coauthors with whom an individual had published) and brokerage. Burt (2000), in an examination of multiple managerial samples, also found a positive correlation between network size and brokerage—operationalized via constraint.

Network strength, on the other hand is expected to be negatively related to brokerage. Granovetter (1973) made the persuasive argument that weak ties are more likely than strong ties to serve as bridges between otherwise disconnected parts of the network. In contrast, strong ties are likely to be associated with dense collections of redundant ties (Perry-Smith, 2006). This suggests that network strength should be negatively linked to brokerage. Burt (1992) challenged this argument suggesting that it is not the quality of the relationship spanning a chasm that matters, but that a structural hole exists in the first place—whether the hole is spanned by a strong or weak tie is secondary. Although we concur with Burt in that brokerage is a more proximal causal agent than network strength, there is nevertheless good reason to believe that increasing network strength makes it less likely that individuals occupy brokerage positions. Empirical evidence supports this logic. For example, in a study of government employees, Lee and Kim (2011) found a negative correlation between network strength and brokerage—measured via network efficiency. Together, then, we hypothesize a positive relation between network size and brokerage and a negative relation between network strength and brokerage.

Hypothesis 6. Network size is positively related to brokerage.

Hypothesis 7. Network strength is negatively related to brokerage.

Network size and strength are also hypothesized to exhibit relations with closure—network size is expected to be negatively related to closure whereas we expect network strength and closure to be positively linked. Assuming a finite level of time and energy, increasing network size makes it less likely for individuals to be able to interact with all of their contacts, or a subset of them, at the same time, thereby reducing the possibility of closure to occur (Burt, 2000). In addition, increasing network size may serve strategic purposes, such that individuals may divide up their time between different individuals to obtain different resources and to achieve different goals. In essence, this logic suggests that network size coincides with reduced multiplexity of relationships (Louch, 2000), resulting in sets of ties that each serves very different functions (e.g., task advice, strategic information, buy-in, social support; Podolny & Baron, 1997). As a result, closure between contacts is unlikely to occur to the same extent as when networks are smaller. Empirical evidence provides support for this logic (e.g., Moran, 2005;
Mors, 2010; Reagans & McEvily, 2003). For example, Carter and Feld (2004) observed a negative correlation between network size and density in a sample of college students.

Network strength is also expected to relate to density—but positively. According to Louch (2000), as the frequency of contact—one indicator of the strength of a relationship—between an individual and his/her contacts increases, the greater the chance that the contacts themselves form a bond. Assuming limited time resources, people are constrained in the number of strong ties they can maintain at a given point in time causing people with multiple strong ties to spend time with their contacts at the same time (e.g., Parks, Stan, & Eggert, 1983). In addition, ties that are well-established and have a long history—another indicator of the strength of a relationship—tend to settle more often into transitive patterns than ties with a brief history (e.g., Hallinan & Hutchins, 1980; transitivity posits that if \( a \) chooses \( b \) as a friend and \( b \) chooses \( c \) as a friend, then \( a \) will choose \( c \) as a friend; Holland & Leinhardt, 1970). Empirical evidence supports these arguments (e.g., Louch, 2000; Reagans & McElvily, 2003). For example, McFadyen et al. (2009) reported a positive correlation between average tie strength and density. Together, then, we predict a negative relation between network size and closure and a positive relation between network strength and closure.

**Hypothesis 8.** Network size is negatively related to closure.

**Hypothesis 9.** Network strength is positively related to closure.

We also expect that network diversity increases as a function of the size of the network. Intuitively, as the number of members in one’s network increases, so does the likelihood that they represent different functional and social circles. However, given that time and energy are finite resources, there is a limit to the number of ties one can cultivate and maintain. In fact, adding similar (in terms of functional and social category diversity) contacts to one’s network increases operating costs without offering many additional benefits thereby producing negative returns (e.g., McFadyen & Cannella, 2004; Zhou et al., 2009). Therefore, strategic networkers seek to acquire additional ties that provide the greatest returns on their expenditures, and increasing size may not provide meaningful returns if each additional contact is embedded in the same social circles (Aral & van Alstyne, 2011; McPherson et al., 2001). By reaching out to new connections possessing distinct qualities, individuals can maximize the likelihood that these contacts provide access to diverse and unique pools of information and knowledge. Indeed, Ibarra (1995) demonstrated that purposeful network development strategies inject diversity into the network, even those utilizing homophily to expand their network. As a result, there should be a positive association between the size and diversity of a network.

**Hypothesis 10.** Network size is positively related to diversity.

Next, we consider the possibility that brokerage, closure, and diversity mediate the effects of network size on innovation. The idea that the composition and structure of individuals’ networks and the positions they occupy within their social spheres may play an integral role in realizing the benefits associated with increasing network size is not new. Burt (1992), for instance, suggested that although the number of structural holes is likely to be a function of an increase in network size, it is not the number of people one is connected to but the number of disconnected actors that determines whether individuals come to enjoy the benefits of privileged and enhanced access to diverse ideas and of having opportunities to exert control. In other words, size alone does not create an advantage; the advantage comes from the configuration of relationships, the positions that people occupy within the structure, and the types of contacts they are connected to. Thus, network size is only likely to positively
impact innovation to the extent that it provides individuals access to contacts who are different from each other and who are otherwise disconnected thereby creating opportunities for brokerage and reducing closure. Serving as a broker between otherwise disconnected and different parts of one’s network and operating under conditions of reduced closure while being able to tap into diverse social spheres, should directly enhance innovation. Together, then, these arguments suggest that brokerage, closure, and diversity fully mediate the positive effect of network size on innovation.

**Hypothesis 11.** Brokerage, closure, and diversity fully mediate the effects of network size on innovation.

Brokerage and closure are also expected to mediate the effects of network strength on innovation. As with network size, there is some evidence that the benefits attributed to network strength—strong networks serve as a mechanism for the transfer of knowledge, particularly tacit knowledge, and provide access to help and support (Hansen, 1999; Uzzi, 1997)—are a function of the structure of the network (Reagans & McEvily, 2003). Tie strength tends to produce closure—strong ties are more likely to be embedded in dense third-party relationships (Granovetter, 1973; Hansen, 1999)—and it is the emergence of cooperative norms in such dense structures and the internalization of these norms that sets the stage for the successful generation and implementation of creative ideas. Specifically, closure and the cooperative norms that it promotes make it more likely that individuals invest their time and energy in assisting others, that the level of trust emerges that is needed to access resources crucial to the innovative process, and that actions can be efficiently and effectively coordinated within the network (e.g., Krackhardt, 1992; Podolny & Baron, 1997; Reagans & McEvily, 2003). Thus, to the extent that closure enhances innovation, we expect that the positive effect of network strength on innovation will be mediated by closure.

Of course, there is a drawback of having a network populated with predominantly strong ties. Network strength can limit brokerage (Fleming et al., 2007)—strong ties are less likely to serve as bridges between otherwise disconnected parts of the network. This, in turn, limits exposure to diverse information and restricts the ability to exert control—both of which should stifle innovation. Taken together then, the aforementioned arguments suggest that closure might mediate the positive effect of strength on innovation while brokerage may mediate its negative effect.

**Hypothesis 12.** Brokerage and closure fully mediate the effects of network strength on innovation.

**Methods**

**Data collection**

We used multiple search techniques to identify relevant empirical studies examining the linkages between the various social network properties and innovation. First, we performed a search of computerized databases, including PsycARTICLES, Psychology and Behavioral Sciences Collection, PsycINFO, SocINDEX, Communication Abstracts, Business Source Complete, ABI/Inform, ProQuest Digital Dissertations, and Web of Science. We used broad keywords related to the primary concepts, such as “creativity,” “innovation,” and “knowledge creation,” in conjunction with “social/knowledge networks,” “network structure,” and “social capital” as well as terms specifically related to the individual network properties (e.g., “network density,” “network centrality”). The electronic search was supplemented with a manual search of forward references to selected theoretical and empirical articles on social networks and innovation (e.g., Burt, 2004; Perry-Smith & Shalley, 2003). In addition, we manually searched the
reference lists and forward citations of all studies that met our inclusion criteria. Third, we searched national conference programs (e.g., Academy of Management, Strategic Management Society) using the same search terms as noted before. Finally, we contacted selected researchers in the area to obtain current or unpublished studies that may fit our criteria for inclusion. This search yielded 6,128 relevant citations.

From this initial set of articles, we applied additional criteria for inclusion. First, we only included studies at the individual level of analysis eliminating studies, for example, that examined the link between social network properties of teams and innovation (e.g., Leenders, van Engelen, & Kratzer, 2003; Reagans & Zuckerman, 2001) or that focused on interdepartmental or interorganizational networks and outcomes related to innovation (e.g., Hansen, 1999; Tsai & Ghoshal, 1998). Second, to be included, a study had to report on at least one relation between a network property and innovation. Third, we included only studies with original data. In cases where multiple studies utilized the same data set (e.g., Rodan, 2002, 2010; Rodan & Galunic, 2004), we eliminated any redundant studies including only the study that had been published first or constituted the most comprehensive analysis of the underlying data set. We included non-overlapping data from dissertations for four of the samples (Baer, 2010, 2012; Obstfeld, 2005; Perry-Smith, 2006; Tortoriello & Krackhardt, 2010). Fourth, we only included studies that relied on actual network data to derive indicators of the various network properties and excluded studies that used network-type measures without having collected egocentric or complete network data. For example, although Teigland and Wasko (2003) examined the link between frequency of communication (a measure of average strength) and creativity, the frequency measure was not based on previously identified network contacts but rather referred to people in general in the organization (e.g., “coworkers in my location”). Consequently, studies such as these were excluded from our sample. Finally, included studies had to report sample sizes and either a correlation coefficient or enough information to calculate a correlation coefficient. We contacted authors of studies that met all criteria, except the reporting of correlations (e.g., Burt, 2004), obtaining useable data for an additional nine studies.

All authors then independently coded these for inclusion in our final data set based on whether the network and innovation measures in each of the studies were consistent with our definition of these concepts. At this point, we excluded studies that used idiosyncratic indicators of network properties that, in many cases, combined a number of network measures into one overall amalgam (e.g., Casanueva & Gallego, 2010; Sorenson, Rivkin, & Fleming, 2006) making it difficult to discern which network feature ultimately is driving the observed effect. This procedure achieved satisfactory rates of agreement for both the network properties (92% agreement) and the innovation measures (83% agreement), and perfect agreement was reached through subsequent discussion. The final data set contained 45 studies (see Table 1 for a summary of the included studies).

Using a coding scheme based on the definitions of network properties provided by Wasserman and Faust (1994) and the definition of innovation provided by van den Ven (1986) and others, all authors classified all possible effect sizes in each of the 45 studies (studies could contain multiple effect sizes). Some studies included panel data or lagged variables (e.g., McFadyen & Cannella, 2004; McFadyen et al., 2009); in these cases, we only coded those effect sizes for which independent and dependent variables referred to the same time period to be consistent with the other cross-sectional studies in our sample.

**Operationalization of variables**

*Network size* reflects a count of the number of ties present in an individual’s network.
Table 1. Summary of papers included in meta-analysis.

<table>
<thead>
<tr>
<th>Studies</th>
<th>Innovation measure</th>
<th>Network type</th>
<th>Network properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anderson (2006)</td>
<td>Self- &amp; other-rating</td>
<td>Ego network</td>
<td>Brokerage (betweenness centrality, other), number of weak ties</td>
</tr>
<tr>
<td>2. Audretsch, Aldridge, &amp; Sanders (2011)</td>
<td>Startup formation</td>
<td>Ego network</td>
<td>Number of strong ties</td>
</tr>
<tr>
<td>3. Baer (2010, 2012)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Strength, diversity (functional), size, number of strong ties</td>
</tr>
<tr>
<td>5. Beaudry &amp; Kananian (2013)</td>
<td>Forward citation count</td>
<td>Complete network</td>
<td>Brokerage (betweenness centrality)</td>
</tr>
<tr>
<td>11. Chen &amp; Gable (2013)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size</td>
</tr>
<tr>
<td>13. Chua (2011)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size, strength, closure (overall network density, alter density), diversity (social category)</td>
</tr>
<tr>
<td>17. Gonzalez-Brambila, Veloso, &amp; Krackhardt (2013)</td>
<td>Publication count</td>
<td>Complete network</td>
<td>Size, strength, brokerage (other), closure (overall network density)</td>
</tr>
<tr>
<td>18. Keri (2011)</td>
<td>Self-rating</td>
<td>Ego network</td>
<td>Size, number of strong ties</td>
</tr>
<tr>
<td>22. Li, Liao, &amp; Yen (2013)</td>
<td>Forward citation count</td>
<td>Complete network</td>
<td>Size, brokerage (betweenness centrality)</td>
</tr>
<tr>
<td>Studies</td>
<td>Innovation measure</td>
<td>Network type</td>
<td>Network properties</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-------------------------------------</td>
<td>--------------------</td>
<td>-------------------------------------------------------------</td>
</tr>
<tr>
<td>23. Liao (2011)</td>
<td>Research awards, forward citation count</td>
<td>Complete network</td>
<td>Strength</td>
</tr>
<tr>
<td>27. Ma, Huang, &amp; Shenkar (2011)</td>
<td>Self-rating</td>
<td>Ego network</td>
<td>Strength</td>
</tr>
<tr>
<td>31. Mehra, Kilduff, &amp; Brass (2001)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size, brokerage (betweenness centrality)</td>
</tr>
<tr>
<td>32. Moran (2005)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size, strength, closure (alter density)</td>
</tr>
<tr>
<td>33. Mors (2010)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size, closure (overall network density)</td>
</tr>
<tr>
<td>34. Obstfeld (2005)(a)</td>
<td>Self-rating</td>
<td>Ego network</td>
<td>Size, brokerage (constraint), closure (overal network density)</td>
</tr>
<tr>
<td>36. Perry-Smith (2006)(a)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Strength, brokerage (betweenness centrality), diversity (functional, social category), number of strong &amp; weak ties</td>
</tr>
<tr>
<td>37. Rhee &amp; Ji (2011)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Number of weak ties</td>
</tr>
<tr>
<td>38. Rodan &amp; Galunic (2004)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size, closure (alter density), diversity (functional), number of strong ties</td>
</tr>
<tr>
<td>39. Rost (2011)</td>
<td>Patent count, forward citation count</td>
<td>Complete network</td>
<td>Brokerage (other), strength</td>
</tr>
<tr>
<td>41. Schultz &amp; Schreyogg (2013)</td>
<td>Forward citation count</td>
<td>Ego network</td>
<td>Number of strong and weak ties</td>
</tr>
<tr>
<td>42. Tortoriello &amp; Krackhardt (2010)(a)</td>
<td>Patent count</td>
<td>Ego network</td>
<td>Size, brokerage (constraint, efficiency, betweenness centrality, number of strong ties</td>
</tr>
<tr>
<td>43. Totterdell, Holman, &amp; Hukin (2008)</td>
<td>Self-rating</td>
<td>Ego network</td>
<td>Size, brokerage (betweenness centrality, other)</td>
</tr>
<tr>
<td>44. Zhou, Shin, Brass, Choi, &amp; Zhang (2009)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Closure (overall network density), number of strong &amp; weak ties</td>
</tr>
<tr>
<td>45. Zou &amp; Ingram (2013)</td>
<td>Other-rating</td>
<td>Ego network</td>
<td>Size, brokerage (constraint)</td>
</tr>
</tbody>
</table>

\(a\)Studies included supplemental data from the dissertation of one of the authors that may not be in the published piece.
Network size includes both the direct connections in egocentric networks as well as the combination of direct and indirect connections in complete networks. We included direct and indirect ties in complete networks as indirect ties have been suggested and shown to provide benefits over and above those provided by direct ties in terms of access to and the mobilization of resources relevant to innovation (e.g., Bian, 1997). In egocentric networks, out-degree centrality, or the number of ties reported by a person, was also considered a measure of network size (Kilduff & Tsai, 2003).

Network strength captures the average strength of all relationships in an individual’s network. The strength of a tie increases as a function of the “amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie” (Granovetter, 1973, p. 1361). Consistent with this definition and previous research (e.g., Ma, Huang, & Shenkar, 2011; Perry-Smith, 2006), we included measures in this category that captured at least one of the following dimensions of strength: duration of the relationship, the frequency of interaction, or the emotional closeness characterizing the relationship.

Network strength is most frequently measured by asking respondents to report how long a particular relationship has been in existence, how often they interact with a particular contact, or how close they feel they are to the other person. The various formative items are then averaged across all ties in the network and used either as separate measures (e.g., Perry-Smith, 2006) or are combined to form one overall indicator of network strength (e.g., Baer, 2010; Ma et al., 2011). When relying on data from publication records, network strength is inferred from the patterns of coauthorship (i.e., the number of times two scientists have coauthored a manuscript together serves as a measure of tie strength by capturing frequency of interaction; e.g., Fleming et al., 2007; McFadyen & Cannella, 2004).

In a number of instances, scholars have used the number of either weak or strong ties to assess the effects of network strength on innovation (e.g., Audretsch, Aldridge, & Sanders, 2011; Perry-Smith, 2006; Zhou et al., 2009). However, such measures confound the strength of a tie (or a set of ties) with the number of ties (see Baer, 2010). As a result, it is not possible to conclusively determine whether any observed effect is due to the strength of a set of relationships or simply due to their number. Consequently, we did not consider number of weak or strong ties as appropriate indicators of network strength and did not incorporate these measures into our path-analytic model. However, given their frequent use in the literature, we report the relevant effect sizes in our meta-analysis for the sake of completeness (see two bottom rows in Table 2 for relevant estimates).

The property of brokerage was formed by clustering a number of measures typically used in the literature. The measures most frequently found in our sample were constraint, or the extent to which people are invested in relationships that lead back to a single contact (Burt, 1992) (constraint was recoded such that higher levels indicate higher levels of brokerage); efficiency, the proportion of non-redundant contacts in a network (Burt, 1992); and betweenness centrality, the extent to which an individual lies on paths between connections taking into account both direct and indirect ties (Freeman, 1977). In addition, we considered more idiosyncratic indicators of brokerage, as long as the variable captured the extent to which an individual served as a bridge between otherwise disconnected parts of the network. For example, Totterdell, Holman, and Hukin (2008) used a measure of gatekeeper brokerage that reflected the number of paths that went through a focal individual and that connected employees from different work groups with the focal individual belonging to the same group as the destination employee.

Network closure reflects the average connectedness of the actors in the network, and is
most commonly operationalized via network density. Network density is a proportional measure reflecting the number of existing ties in the network out of the total number of possible ties (Wasserman & Faust, 1994). Alter density, alternatively, captures the proportion of existing ties out all possible ties among an individual’s contacts, excluding any direct ties (e.g., Moran, 2005).

Finally, consistent with previous research (Jackson et al., 1995; Joshi & Roh, 2009), we distinguished between task- and relations-oriented diversity and clustered both under the property of network diversity. Task-oriented diversity captures diversity with respect to attributes such as functional background, departmental affiliation, or tenure (e.g., Baer, 2010; Perry-Smith, 2006); relations-oriented diversity captures diversity with respect to attributes such as sex, race/ethnicity, or cultural background (e.g., Chua, 2011; Perry-Smith, 2002). Both task- and relations-oriented diversity were most commonly operationalized via Blau’s (1977) index of heterogeneity. In addition, some studies measured diversity by simply counting the number of different categories present among an individual’s contacts. For example, Paruchuri (2010) measured diversity via the count of unique areas of expertise among a focal inventor’s collaborators.

Innovation. Consistent with our definition of innovation, we included any study that offered a measure of idea generation, execution, or both, excluding studies focusing on the sharing or transfer of knowledge or the diffusion of innovations without considering how ideas and knowledge were developed and put into practice in the first place (e.g., Chang & Harrington, 2005; Reagans & McEvily, 2003; Weenig, 1999). Innovation was typically measured in one of two ways—via subjective self/others’ evaluations of a person’s innovation (e.g., Moran, 2005; Rodan & Galunic, 2004) or via more objective indicators, such as the number of patents, publications, and forward citations obtained or the prizes awarded for certain innovative achievements (e.g., Fleming et al., 2007; Liao, 2011).

<table>
<thead>
<tr>
<th>Network properties</th>
<th>k</th>
<th>N</th>
<th>ρ</th>
<th>SDρ</th>
<th>[95% CI]</th>
<th>[80% CV]</th>
<th>Fail safe k</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network size</td>
<td>26</td>
<td>463,601</td>
<td>0.29***</td>
<td>0.17</td>
<td>[0.21, 0.36]</td>
<td>[0.07, 0.51]</td>
<td>348</td>
</tr>
<tr>
<td>Network strength</td>
<td>14</td>
<td>79,375</td>
<td>0.18***</td>
<td>0.05</td>
<td>[0.13, 0.22]</td>
<td>[0.11, 0.24]</td>
<td>109</td>
</tr>
<tr>
<td>Brokerage</td>
<td>24</td>
<td>362,141</td>
<td>0.33***</td>
<td>0.12</td>
<td>[0.27, 0.39]</td>
<td>[0.17, 0.49]</td>
<td>371</td>
</tr>
<tr>
<td>Constraint</td>
<td>7</td>
<td>144,827</td>
<td>0.17***</td>
<td>0.08</td>
<td>[0.06, 0.27]</td>
<td>[0.06, 0.27]</td>
<td>51</td>
</tr>
<tr>
<td>Efficiency</td>
<td>6</td>
<td>2,870</td>
<td>0.55***</td>
<td>0.33</td>
<td>[0.29, 0.73]</td>
<td>[0.13, 0.96]</td>
<td>158</td>
</tr>
<tr>
<td>Betweenness centrality</td>
<td>11</td>
<td>17,190</td>
<td>0.34***</td>
<td>0.30</td>
<td>[0.12, 0.53]</td>
<td>[0.35, 0.73]</td>
<td>175</td>
</tr>
<tr>
<td>Alter density</td>
<td>6</td>
<td>199,037</td>
<td>0.22***</td>
<td>0.02</td>
<td>[0.16, 0.28]</td>
<td>[0.19, 0.25]</td>
<td>59</td>
</tr>
<tr>
<td>Closure</td>
<td>12</td>
<td>255,428</td>
<td>-0.10*</td>
<td>-0.03</td>
<td>[-0.19, 0.00]</td>
<td>[-0.23, 0.03]</td>
<td>—</td>
</tr>
<tr>
<td>Overall network density</td>
<td>8</td>
<td>18,428</td>
<td>-0.06*</td>
<td>-0.16</td>
<td>[-0.23, 0.18]</td>
<td>[-0.23, 0.18]</td>
<td>—</td>
</tr>
<tr>
<td>Alter density</td>
<td>5</td>
<td>237,210</td>
<td>-0.10*</td>
<td>-0.03</td>
<td>[-0.12, 0.00]</td>
<td>[-0.13, 0.00]</td>
<td>2</td>
</tr>
<tr>
<td>Network diversity</td>
<td>9</td>
<td>223,912</td>
<td>0.24***</td>
<td>0.11</td>
<td>[0.14, 0.33]</td>
<td>[0.10, 0.38]</td>
<td>99</td>
</tr>
<tr>
<td>Functional</td>
<td>7</td>
<td>223,630</td>
<td>0.27***</td>
<td>0.11</td>
<td>[0.16, 0.37]</td>
<td>[0.13, 0.41]</td>
<td>86</td>
</tr>
<tr>
<td>Social category</td>
<td>3</td>
<td>379</td>
<td>0.09</td>
<td>0.11</td>
<td>[-0.07, 0.24]</td>
<td>[-0.05, 0.23]</td>
<td>—</td>
</tr>
<tr>
<td>Number of strong ties</td>
<td>8</td>
<td>1,273</td>
<td>0.23***</td>
<td>0.23</td>
<td>[0.07, 0.39]</td>
<td>[-0.06, 0.52]</td>
<td>85</td>
</tr>
<tr>
<td>Number of weak ties</td>
<td>7</td>
<td>731</td>
<td>0.12</td>
<td>0.42</td>
<td>[-0.22, 0.44]</td>
<td>[-0.41, 0.66]</td>
<td>—</td>
</tr>
</tbody>
</table>

*^k = number of studies, N = aggregated sample size, ρ = mean estimate of corrected population correlation, SDρ = estimated standard deviation of corrected population correlation, 95% CI = 95% confidence interval, 80% CV = 80% credibility interval, Fail safe k = number of unpublished studies with null effect sizes that would be needed to reduce the effect size to nonsignificance.

+ p < .10; *p < .05; **p < .01; ***p < .001.
To be included, subjective indicators of innovation had to capture idea generation, execution, or both. Examples include respondents’ self-assessment of their involvement in a set of innovations (e.g., Obstfeld, 2005), supervisor ratings of the extent to which employees had developed ideas for new product or service offerings (e.g., Baer, 2010; Perry-Smith, 2006), or judge/supervisor ratings of the creativity of individuals’ ideas or proposals (e.g., Burt, 2004; Chua, 2011). In selected circumstances, we also included measures that combined items on innovation with those of general performance. This was done when there was explicit evidence that the results for innovation were not affected by the inclusion of items on performance or when performance in the domain under investigation itself required the development and implementation of new ideas (e.g., Mehra et al., 2001).

In addition, we also included studies that used more objective indicators, such as patent counts, to gauge innovation. Patents reflect original contributions or novel recombination of existing knowledge and are frequently used to measure individual innovation (Griliches, 1990; Pavitt, 1985). In applying for a patent, inventors must prove the novelty and utility to an examiner, providing support for the innovativeness of the claim. Similarly, we considered publication counts—an indicator often used to assess scientific productivity (e.g., Azoulay, Ding, & Stuart, 2009; Ding, Levin, Stephan, & Winkler, 2010)—as a measure of the extent to which a person had generated and contributed a new idea to a domain of scientific inquiry. In cases in which publication counts were differentiated by author position, we included those counts that most directly reflected a person’s innovation. For example, in the biomedical sciences, last-authored papers are more reflective of individual innovation than first-authored papers as the last author is typically the one who determines the research question to be investigated and is responsible for obtaining funding (e.g., McFadyen et al., 2009). We considered both unweighted as well as weighted counts of patents and publications as weighting provides additional information about the novelty and usefulness of an innovation (Frey & Rost, 2010; Stephan & Levin, 1991). Journal impact factors are typically used to weight publication counts (e.g., McFadyen & Cannella, 2004); citations are typically used to weight patent counts (e.g., Lee, 2010). Finally, we also included measures of forward citations—citations subsequently referencing a previous patent or publication—as objective indicators of innovation. Forward citations are frequently considered a measure of whether an idea provides a useful and reliable foundation for future insights (Frey & Rost, 2010; Reedijk, 1998), reflecting both its novelty and usefulness in action (Albert, Avery, Narin, & McAllister, 1991; Lanjouw & Schankerman, 2004; Trajtenberg, 1990).

Meta-analytic procedure

Following procedures by Hunter and Schmidt (2004), we corrected observed correlations for measurement and sampling error. To correct for measurement unreliability in self and other ratings of innovation, we used Cronbach’s alpha coefficients reported in the studies. Whenever a study did not provide the necessary reliability estimates, we used the average of the available reliability estimates from other studies in our sample that reported on the same type of correlation. To avoid over-correction, we did not adjust the objective indicators of innovation, such as the number of patents, publications, or forward citations for measurement unreliability.

To maintain independence of effect sizes, we combined correlations from studies that provided more than one correlation per network feature (i.e., size, strength, constraint, efficiency, betweenness centrality, overall network density, alter density, task-oriented diversity, relations-oriented diversity). For example, Burt (2004) reported correlations between network
constraint and multiple indicators of innovation. In such and other cases, we combined the various correlations into one overall effect size using the procedure outlined by Rosenthal and Rubin (1986). In addition, because we clustered certain network features into categories (i.e., size, strength, brokerage, closure, diversity), it is possible that a single study contributes more than one correlation to the same property. For instance, Liu (2011) reported correlations between innovation and two indicators of brokerage: efficiency and betweenness centrality. To ensure independence, we again used Rosenthal and Rubin’s (1986) formula to combine correlations, such that a study may only contribute one effect size per network category.

We used a random effects model correcting for sampling error by weighting each study’s effect size by its sample size (Hunter & Schmidt, 2002). A random effects model allows the population effect size to vary between studies and protects from Type I error rate inflation. We also computed the 95% confidence interval (CI) and the 80% credibility interval (CV) around the sample-weighted mean correlation. Confidence intervals provide an estimate of the variability around the estimated average correlation due to sampling error. Credibility intervals provide an estimate of the variability in the distribution of the average correlation and constitute a test of heterogeneity (Hunter & Schmidt, 2004; Whitener, 1990). Typically, researchers calculate a Q-statistic to test for heterogeneity in observed correlations across studies (Hedges & Olkin, 1985). However, when there is large variation in sample sizes across studies, the Q-statistic may be inflated (Hunter & Schmidt, 2004). The sample sizes in our study ranged from 34 to 183,204 and, therefore, the Q-statistics may not accurately reflect whether true heterogeneity exists. Consequently, we inspected the credibility intervals to assess heterogeneity in a given relation. Previous research suggests that a random-effects model provides more accurate estimates than fixed-effects models when there is heterogeneity (Cheung & Chan, 2005; Overton, 1998).

**Meta-analytic path analysis**

To test our overall model, we conducted a meta-analytic path analysis, which requires estimates of the correlations between all variables involved in the analysis (e.g., Shadish, 1996; Viswesvaran & Ones, 1995). Based on the studies included in our sample, however, we were able to construct only a partial meta-analytic correlation matrix. Given that there is no previous meta-analysis that, at least to our knowledge, has examined the magnitude of relations between the various network features considered in the present study, we conducted a second meta-analysis to obtain estimates of the missing correlations and to supplement the 16 studies in our sample that reported correlations. To ensure that these studies represented the same population of studies as those included in our primary meta-analysis, we searched the top journals of those scientific areas represented in our sample (management, psychology, sociology, political science) and those journals that frequently publish relevant social network studies. These journals included *Academy of Management Journal, Administrative Science Quarterly, American Journal of Political Science, American Journal of Sociology, American Sociological Review, Journal of Applied Psychology, Management Science, Organization Science, Research Evaluation, Research Policy, Scientometrics, Social Networks,* and *Strategic Management Journal*. A search using a similar set of keywords as in our initial search yielded an additional 1,034 studies.

As before, we only included studies at the individual level of analysis containing original data. Second, to be included, a study had to report at least one correlation between two of the network properties included in the previous coding scheme. Third, we only included studies that relied on actual network data.
Finally, included studies had to report sample sizes and either a correlation coefficient or enough information to calculate a correlation coefficient. These criteria resulted in the inclusion of an additional 38 studies.

We used the same meta-analytic procedures (Hunter & Schmidt, 2004) to estimate the relevant correlations between the five network properties. Consistent with our previous approach, we did not correct network measures for unreliability. We used the created correlation matrix to run a path analysis, using maximum-likelihood estimation. Means and standard deviations for each variable were set to 0 and 1, respectively. The number of observations was determined by calculating the harmonic mean of the sample sizes (N = 32,541) from the meta-analytic estimates (Viswesvaran & Ones, 1995). To evaluate model fit, we used established fit indices—chi-square (χ²), the comparative fit index (CFI), the root-mean-square error of approximation (RMSEA), the standardized root-mean square residual (SRMR), and Akaike’s Information Criterion (AIC). Commonly recommended cutoff values were used to evaluate fit (CFI > .90, RMSEA < .08, and SRMR < .10; Kline, 2005).

Results

Meta-analytic results

Table 2 summarizes the meta-analytic relations between the five network properties (as well as their various operationalizations) and innovation. Hypothesis 1 predicted a positive relation between network size and innovation. Consistent with our expectation, there was a significant, positive association between the two variables (\( \hat{\rho} = .29, p < .001, k = 26, 95\% \text{ CI} = [.21, .36] \)). Thus, Hypothesis 1 was supported.

Hypothesis 2 made competing predictions regarding the nature of the link between network strength and innovation, suggesting that strength could have either a positive (Hypothesis 2a) or a negative association with innovation (Hypothesis 2b). Consistent with Hypothesis 2a, there was a significant, positive relation between the two variables (\( \hat{\rho} = .18, p < .001, k = 14, 95\% \text{ CI} = [.13, .22] \)). Therefore, there was support for Hypothesis 2a; Hypothesis 2b was not supported.³

Hypothesis 3 predicted that brokerage and innovation would be positively related. This hypothesis was supported. Correlations both for overall brokerage (\( \hat{\rho} = .33, p < .001, k = 24, 95\% \text{ CI} = [.27, .39] \)) and for each of the different operationalizations of brokerage—constraint (\( \hat{\rho} = .17, p < .001, k = 7, 95\% \text{ CI} = [.06, .27] \)), efficiency (\( \hat{\rho} = .55, p < .001, k = 6, 95\% \text{ CI} = [.29, .73] \)), betweenness centrality (\( \hat{\rho} = .34, p < .01, k = 11, 95\% \text{ CI} = [.12, .53] \)), and the “other” category (\( \hat{\rho} = .22, p < .001, k = 6, 95\% \text{ CI} = [.16, .28] \)) were positive and statistically significant.

Hypothesis 4 made competing predictions regarding the nature of the link between closure and innovation, suggesting that closure may either have a positive (Hypothesis 4a) or a negative relation with innovation (Hypothesis 4b). Although there was a significant, negative relation between alter density and innovation (\( \hat{\rho} = -.06, p < .05, k = 5, 95\% \text{ CI} = [-.12, .00] \)), overall network density (\( \hat{\rho} = -.03, k = 8, 95\% \text{ CI} = [-.23, .18] \)), as well as overall closure (\( \hat{\rho} = -.10, k = 12, 95\% \text{ CI} = [-.19, .00] \)) exhibited nonsignificant relations with innovation. Thus, there was only weak support for Hypothesis 4b; Hypothesis 4a was not supported.

Hypothesis 5 proposed a positive association between network diversity and innovation. Consistent with our expectation, there was a significant, positive correlation between the two variables, both for overall network diversity (\( \hat{\rho} = .24, p < .001, k = 9, 95\% \text{ CI} = [.14, .33] \)) and when operationalized via task-oriented diversity (\( \hat{\rho} = .27, p < .001, k = 7, 95\% \text{ CI} = [.16, .37] \)). However, relations-oriented diversity did not relate significantly to innovation (\( \hat{\rho} = .09, k = 3, 95\% \text{ CI} = [-.07, .24] \)). Thus, there was good support for
Hypothesis 5, particularly when diversity was focused on task-oriented characteristics, such as expertise and tenure.\textsuperscript{4,5}

**Path-analytic results**

In Hypotheses 6 through 12 we predicted that the effects of network size and strength on innovation would be fully mediated by brokerage, closure, and diversity. We tested the proposed model (see Figure 1) via path analysis inputting the meta-analytic correlation matrix displayed in Table 3. As shown in Table 4, the model fit of the hypothesized model was not satisfactory, $\chi^2 (6) = 2,356.32$, CFI = .93, RMSEA = .11, SRMR = .05, AIC = 2,386.32. All paths, however, were significant and in the predicted direction.

Given that network strength has been suggested to exert positive effects on innovation but our model captured and revealed only its negative, indirect effects via brokerage and closure, we explored the possibility that the positive effects on innovation ascribed to network strength may operate directly rather than indirectly. Hence, we included a direct path from network strength to innovation. As shown in Table 4, this alternative model had excellent fit, $\chi^2 (5) = 442.13$, CFI = .99, RMSEA = .05, SRMR = .02, AIC = 474.12 and fit the data significantly better than the hypothesized model, $\Delta\chi^2 (1) = 1,914.19$, $p < .01$. It is this model on which all tests of direct and indirect effects are based on (see Figure 2).

Figure 2 displays the standardized coefficients for our final path model. Consistent with Hypotheses 6 and 8, respectively, network size had a significant, positive effect on brokerage ($\beta = .70$, $p < .01$) and a significant, negative effect on closure ($\beta = -.19$, $p < .01$). In addition and consistent with Hypothesis 10, there was a significant, positive direct effect of size on diversity ($\beta = .24$, $p < .01$). Also as expected, network strength had a significant, positive effect on closure ($\beta = .24$, $p < .01$) and a significant, negative effect on brokerage ($\beta = -.06$, $p < .01$), supporting both Hypotheses 7 and 9, respectively.

Confirming Hypothesis 11, the effect of network size on innovation was completely mediated by brokerage, closure, and diversity ($\beta = .27$, $p < .01$). However, failing to support Hypothesis 12, the effect of strength on innovation was only partially mediated by brokerage and closure ($\beta = -.04$, $p < .01$), as there was a significant, positive and direct effect of strength on innovation ($\beta = .23$, $p < .01$) over and above the indirect effects. In sum, these results suggest that positional (e.g., brokerage), structural (e.g., density), and nodal (e.g., functional background) network features fully or partially mediate the effects of network size and strength on innovation (see Table 5).

**Discussion**

The purpose of the present study was to systematically review and integrate the fragmented literature on the link between social networks and individual innovation using meta-analytic methods. Building on previous theory and research, we offered an approach to clustering the variety of different ways in which network characteristics have been operationalized in the past into five general properties: size, strength, brokerage, closure, and diversity. This approach allowed us to succinctly summarize and compare the effects on individual innovation associated with each of the five properties. Our analysis suggests that brokerage has the strongest positive relation with innovation, followed by network size, network diversity (particularly, task-oriented diversity), and strength all of which exhibited weak-to-moderate relations with individual innovation. Closure was negatively related to innovation, albeit only marginally so.

In addition to using meta-analysis to estimate the true population effect sizes associated with each of the network properties, we also offered a path-analytic integration of these properties, specifying the direct and indirect
Table 3. Meta-analytic correlations for path analysis.\(^a\)

<table>
<thead>
<tr>
<th>Variable</th>
<th>(\hat{\rho})</th>
<th>[95% CI]</th>
<th>(\hat{\rho})</th>
<th>[95% CI]</th>
<th>(\hat{\rho})</th>
<th>[95% CI]</th>
<th>(\hat{\rho})</th>
<th>[95% CI]</th>
<th>(\hat{\rho})</th>
<th>[95% CI]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Network size</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>2. Network strength</td>
<td>.01</td>
<td>[-.05, .08]</td>
<td>14</td>
<td>62,936</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Brokerage</td>
<td>.70</td>
<td>[.61, .78]</td>
<td>-.05</td>
<td>[-.29, .19]</td>
<td>14</td>
<td>312,775</td>
<td>3</td>
<td>2,932</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Innovation</td>
<td>.29</td>
<td>[.21, .36]</td>
<td>.18</td>
<td>[.13, .22]</td>
<td>.33</td>
<td>[.27, .39]</td>
<td>-.10</td>
<td>[-.19, .00]</td>
<td>.24</td>
<td>[.14, .33]</td>
</tr>
</tbody>
</table>

\(^a\)\(\hat{\rho}\) = mean estimate of corrected population correlation, 95% CI = 95% confidence interval, \(k\) = number of studies, \(N\) = aggregated sample size.

Table 4. Fit statistics for alternative models.\(^a\)

<table>
<thead>
<tr>
<th>Model</th>
<th>(\chi^2)</th>
<th>df</th>
<th>(\Delta\chi^2)</th>
<th>CFI</th>
<th>RMSEA</th>
<th>SRMR</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theoretical model (Figure 1)</td>
<td>2356.32</td>
<td>6</td>
<td>-</td>
<td>.93</td>
<td>.11</td>
<td>.05</td>
<td>2386.32</td>
</tr>
<tr>
<td>Alternative model(^b) (Figure 2)</td>
<td>442.13</td>
<td>5</td>
<td>1914.19(^{**})</td>
<td>.99</td>
<td>.05</td>
<td>.02</td>
<td>474.12</td>
</tr>
</tbody>
</table>

\(^a\)\(N = 32,541;\)\(^b\)adds direct path from network strength to innovation; \(^c\)model fit compared with previous model.\(^p < .05;\)\(^{**}p < .01.\)
effects through which they impact innovation. Specifically, we offered a comprehensive model highlighting that the distal antecedents of network size and strength impact innovation through the more proximal features of brokerage, closure, and network diversity. Relying on meta-analytic path analysis, we tested this model and found general support for its validity. Consistent with our logic, network size and strength impacted innovation through a web of relations with the more proximal positional, structural, and nodal features of brokerage, closure, and diversity. These more proximal network properties, in turn, served to mediate the effects of network size and strength on innovation either fully, as in the case of network size, or partially, as in the case of network strength.

The direct positive effect of network strength on innovation—which was further validated by the finding that the number of strong ties was positively related to innovation in contrast to the number of weak ties, which exhibited a nonsignificant relation with innovation—highlights an interesting tension in the way network strength shapes innovation at work. On the one hand, strong ties are likely to result in closure and reduced brokerage thereby limiting access to individuals with heterogeneous information and knowledge sets, which should ultimately reduce the potential to develop novel, useful ideas and solutions. On the other hand, the trust and solidarity associated with strong ties is not only likely to be helpful in mobilizing the support necessary to act upon one’s ideas (Baer, 2012; Kanter, 1988), but strong ties are also likely to be helpful when the knowledge to be transmitted is more tacit in nature (Hansen, 1999), such as the knowledge involved in formulating problems. Indeed, work by Cross and Sproull (2004) has shown that tie strength relates negatively to knowledge about solutions but positively to knowledge about problem reformulation and validation of one’s ideas. In fact, the results of our path analysis suggest that the negative, indirect effect of network strength on innovation is relatively small as compared to its positive, direct effect. Thus, when the outcome organizations care

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**Figure 2.** Final model of network effects on innovation.a

*Standardized coefficients in the final model (alternative Model 2) are presented; N = 32,541.

*p < .05; **p < .01.

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**Table 5.** Direct, indirect, and total effects of network size and strength on innovation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Direct effects</th>
<th>Indirect effects</th>
<th>Total effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network size</td>
<td>—</td>
<td>.27**</td>
<td>.27**</td>
</tr>
<tr>
<td>Network strength</td>
<td>.23**</td>
<td>−.04**</td>
<td>.19**</td>
</tr>
</tbody>
</table>

*Standardized coefficients in the final model (alternative model; Figure 2) are presented; harmonic N = 32,541.

*p < .05; **p < .01.
about requires the development and implementation of fresh ideas, the trust and solidarity benefits associated with tie strength may outweigh the costs associated with reduced access to heterogeneous information and knowledge sets. This conclusion is echoed by a number of recent studies, all of which point towards the conclusion that strong ties seem to be more beneficial to innovation than weak ties (e.g., Kijkuit & van den Ende, 2010), particularly when embedded in a network structure that allows individuals to serve as brokers between disconnected others combining the best of both worlds—access to heterogeneous knowledge sets and trust to key communication and exchange partners (McFadyen et al., 2009; Rost, 2011).

The argument often advanced in the extant literature that the benefits associated with network closure enhance innovation was not supported—closure exhibited a significantly negative effect on innovation. It appears that the benefits of dense network structures for coordinating action and for garnering support are outweighed by the downsides of such structures—redundant access to information, reduced willingness to take risks, and the adherence to existing norms and expectations. Alternatively, it is possible that the positive direct effect of strength that we observed captured the effect of trust and solidarity on innovation. This interpretation is consistent with work by Moran (2005) who observed that network strength (the closeness and trust associated with interpersonal relationships) was a significant predictor of managerial innovation whereas the density of the network was not. Thus, rather than closing one’s network, building deep and meaningful dyadic relationships seems to be the key conduit for obtaining the trust and support necessary for engaging the innovative process.

One major contribution of the present study is that we partially reconcile the two perspectives on the effects of networks on innovation that often have been contrasted as polar opposites—brokerage versus closure. Although it is true that brokerage had uniformly positive effects and closure had uniformly negative effects on innovation, network strength—a direct antecedent to closure—did exhibit both positive and negative effects as reflected in our competing Hypotheses 2a and 2b. These findings hint at the potential value not only of integrating the two perspectives—the effects of closure were significant while controlling for the effects of brokerage—but also of acknowledging that given the dual nature of innovation, certain network properties, such as strength can have positive and negative effects on innovation simultaneously. Although network strength had a net positive effect on innovation, it did produce closure, which then undermined innovation. This finding challenges previously held assumptions and reminds scholars to embrace the complexities of the relations between social network properties and innovation in their theorizing and measurement.

Practical implications

Our results offer some guidance as to how individuals should craft their networks. Expanding the size of one’s network is important as adding people to one’s social spheres is likely to increase the opportunities for brokerage and/or to reduce closure and, at the same time, makes it more likely that one gets exposed to and has access to a greater variety of people with different information and knowledge sets. Naturally, given the demands that an ever-increasing web of contacts may place on the focal individual—both in terms of cognitive and time resources—there will be diminishing return to this strategy, as has been well documented (Baer, 2010; McFadyen & Cannella, 2004). The key then is to nurture a manageable number of direct relationships to what Uzzi and Dunlap (2005) have termed superconnectors—powerful brokers who are likely to provide us with access to a wide array of different social circles. Quality, however, should not be sacrificed for
quantity. Network strength is a powerful force in boosting innovation and thus forging ahead with building a vast network while not investing in each relationship is likely to provide relatively limited returns. Weak ties may be useful for learning about new ideas (e.g., Perry-Smith, 2006), but strong ties are instrumental in identifying and formulating problems in the first place (e.g., Cross & Sproull, 2004), transmitting more sensitive and tacit knowledge often required for innovative ideas (e.g., Hansen, 1999), and for building support to realize the idea (e.g., Baer, 2012). Although we acknowledge that strong ties may be most potent when embedded in a network rich in structural holes—a notion that we could not test in the present study (see Limitations section)—our findings corroborate the conclusion by Rost (2011) that strong ties benefit innovation independent of the structure in which they are embedded.

Limitations and avenues for future research

Our study has a number of limitations that are worth noting. First, in our theoretical and empirical analysis we assumed that the relations between the various network features and innovation are linear. However, ample research suggests that a number of network characteristics, including network size (e.g., Baer, 2010), strength (e.g., McFadyen & Cannella, 2004; Zhou et al., 2009), brokerage (e.g., Rost, 2011), the extent to which individuals occupy positions between the core and periphery of the network (e.g., Cattani & Ferriani, 2008), and the extent to which networks exhibit properties of a small world (e.g., Uzzi & Spiro, 2005) exhibit inverted U-shaped relations to outcomes, such as creativity and innovation. Unfortunately, given the relatively few studies that have examined each feature (and their non-linear relations), we were not able to meta-analytically review the potentially quadratic nature of these relations and thus focused on the linear effects exclusively. Nevertheless, we recognize that many of the features examined here may very well exhibit inverted U-shaped relations with innovation. For example, we highlighted the potential benefits of network strength for innovation. However, as average tie strength increases to the extent that networks are populated mostly by friends who have known each other for years and who communicate on a daily basis, the costs associated with increasing network strength may ultimately outweigh its trust and solidarity benefits (McFadyen & Cannella, 2004). Consequently, as more studies examining these nonlinear relations become available, we encourage future meta-analytic efforts to explicitly consider the nonlinear nature of most of the associations considered in the present paper.

Second, although we were not able to examine the extent to which various network features differentially impact the generative aspect of innovation versus the refinement and execution components—most studies in our sample did not consider this distinction—there is evidence to suggest that certain network constellations may be more critical during some phases of the innovation process than others (e.g., Lavie & Drori, 2012). For instance, work by Kijkuit and van den Ende (2010) suggests that whereas larger networks may be conducive to the generative phase of the innovation process, networks of smaller size may be more helpful during the latter stages. In addition, whereas lack of closure seems to be critical during idea generation, during the latter stages of the innovation process networks of greater density seem to be relatively more helpful. Our ability to detect such nuances was limited by the lack of available studies and data. Thus, we encourage future research to examine more systematically the coevolution of innovative ideas and their associated networks to uncover the differential effects that certain network features may have over time and how individuals manage these dynamics.
Next, many studies in our sample examined ties that deliver informational benefits primarily, or constructed their network measures by aggregating across various tie types. Naturally, focusing on one type of relationship or aggregating across various types of ties may obfuscate the fact that different types of relationships may exert different effects. A study by Podolny and Baron (1997) nicely illustrates this point. These authors showed that the effect of brokerage on promotions was positive for ties that served as conduits for information but was negative for buy-in ties—ties that conveyed expectations and identity. Given these findings, Podolny and Baron (1997) concluded, “the standard practice in network research of aggregating disparate kinds of ties when relating network structure to mobility outcomes seems ill-conceived” (p. 689). We echo this sentiment, as the different effects of disparate kinds of ties are unlikely to be confined to issues of mobility but are likely to extend to other domains, such as innovation. We thus would encourage future research to more systematically consider the role that tie type and the content conveyed through ties may play in determining the effects of certain network features on innovation.

Fourth, the focus of our path-analytic integration was on specifying and estimating the indirect pathways through which basic network features, such as size and strength may affect innovation. In doing so, we have ignored the role of potential moderators of these relations. However, previous research has highlighted that some network features may serve to enhance the effects of certain other network characteristics. For example, we know that network strength provides more substantial returns for knowledge creation and innovation when strong ties are embedded in networks rich in structural holes (McFadyen et al., 2009; Rost, 2011). In addition, previous work has suggested that brokerage is a more powerful driver of individual innovation when networks are composed of individuals with heterogeneous information and knowledge sets (Rodan & Galunic, 2004). In addition, there is a growing body of evidence suggesting that individual differences capturing people’s proclivity to utilize the various resources accessible through one’s social relationships (Anderson, 2008; Baer, 2010; Zhou et al., 2009), such as openness to experience or need for cognition may serve to enhance the effects of, for example, network size and strength on innovation and related outcomes. However, due to the relatively few studies that have considered network characteristics or personality differences as potential moderators, we were not able to test our mediating pathways for different levels of these moderating variables. Future research may want to test our model in different populations or environments that systemically vary in personality or network characteristics.

Fifth, there was a fair amount of heterogeneity in the observed relations as evidenced by the sometimes relatively wide 80% credibility intervals. As a rule of thumb, if a credibility interval is either wide or contains zero, the existing heterogeneity may be indicative of the fact that moderators are operative (Whitener, 1990). To ameliorate concerns regarding the operation of moderators but given the fact that only very few potential moderating variables were consistently reported across studies, we examined the role of three methodological artifacts as potential moderators. Specifically, in addition to distinguishing between the type of network data (egocentric network vs. complete network) as reported in Endnote 3, we also distinguished between subjective criterion measures (self- and other-ratings) and objective measures (patent/publication counts, citations; Hülsheger et al., 2009), and coded for publication status (published vs. unpublished). None of these methodological moderators, however, accounted for significant amounts of heterogeneity in the reported relations. Given the lack of results for the moderating variables considered here, we would encourage scholars...
to identify and examine both methodological and substantive moderating variables as they continue to study the relations between network properties on the one hand and innovation on the other.

Finally, although our study provides an important step forward in understanding the various ways in which social network characteristics impact innovation, our theoretical and empirical analysis still relies on a number of unobserved mechanisms. For example, we argued that brokerage should boost innovation due to informational and control benefits, yet such benefits remained unobserved. Similarly, network strength was found to directly impact innovation presumably due to benefits associated with trust and solidarity allowing for the exchange of more sensitive information and access to buy-in but again, we were not able to verify the validity of these mechanisms. Most studies do not directly examine the linkages between network features and the types of resources being accessed or transmitted via the respective ties (for an exception, see Anderson, 2008) and so our arguments about the precise mechanisms remain somewhat speculative. We believe that it is worth examining these mechanisms in more detail and we encourage future research to do so.

**Conclusion**

The results of our meta-analysis show that most network features examined over the past two decades exhibit robust and mostly positive correlations (with the exception of closure) with individual innovation at work. Our path-analytic integration suggests that two basic features of social networks—the number and average strength of ties—operate through the positional and structural features of brokerage and closure as well as through diversity to impact innovation. While size (via brokerage, closure, and diversity) exerts positive effects on innovation only, network strength serves as a double-edged sword—it fosters network closure and inhibits brokerage, which constricts access to diverse information and knowledge sets but it also promotes trust and solidarity, which boosts innovation with the net effect of strength being positive.

**Notes**

1. Only four studies included measures with both direct and indirect ties. To examine whether there may be systematic differences in effect sizes associated with network size based on direct versus direct and indirect ties, we conducted a subgroup analysis. No significant differences were found ($Q_b = 2.00, ns$).

2. We did not set any inclusion criterion for the reach of the indirect network as researchers typically do not specify or report cutoffs for the size of the indirect network. Thus, we included all studies that reported effect sizes for the relation between network size and innovation. However, we do recognize that there may be heterogeneity among studies in terms of how far removed indirect ties are from ego.

3. Inspection of Table 2 also revealed that the number of strong ties had a positive relation to innovation ($\hat{\rho} = .23, p < .01, k = 8, 95\% CI = [.07, .39]$), whereas the number of weak ties was unrelated to innovation ($\hat{\rho} = .12, k = 7, 95\% CI = [−.22, .44]$).

4. For the three properties (i.e., brokerage, closure, diversity) for which we explicitly distinguished between the different ways in which each property had been measured, we conducted subgroup analysis to see if the effect sizes varied within each property. $Q_b$ indicates whether effect sizes vary between subgroups (Hunter & Schmidt, 2004). There were no differences between the different ways of measuring closure ($Q_b = .99, ns$) and diversity ($Q_b = 1.34, ns$). However, there were significant differences in the brokerage category ($Q_b = 12.82, p < .05$), driven by the significant difference between those studies that used efficiency to measure brokerage ($\hat{\rho} = .55, p < .001$) and those that used either constraint ($\hat{\rho} = .17, p < .001$) or more idiosyncratic measures of brokerage ($\hat{\rho} = .22, p < .001$).
5. We also tested whether there were any differences in effect sizes between those studies that relied on egocentric network data and those that were based upon complete network data. Generally, there were no differences across the various network features, with the exception of network size ($Q_b = 6.30, p < .05$)—the correlation between network size and innovation in egocentric networks was significantly smaller ($\hat{\rho} = .14, p < .05$) than the correlation in complete networks ($\hat{\rho} = .41, p < .001$).

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