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From homophily through embeddedness to strategy: The role of network accuracy in partner selection choices

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Introduction

The literature on inter-organizational collaboration has traditionally emphasized the need for access to external resources to explain partner selection choices by organizations (e.g. Mizruchi, 1992; Pfeffer and Nowak, 1976). Overall, this research tradition has emphasized how access to complementary resources held by others may offer strategic benefits to organizations (Powell et al., 1996; Uzzi, 1996). Notwithstanding these strategic advantages, collaboration also brings risks with it. For example, partners could find out information that the focal organization does not want to disclose, leading to so called unintentional knowledge spillovers (Lavie, 2006). Alternatively or partners could renege on their promises and cause a free-rider problem (Gulati and Singh, 1998; Meuleman et al., 2010). Therefore, firms should take into account the prospective partners' resources, capabilities, trustworthiness and co-operativeness during partner selection decisions (Gulati, 1995). However, given the paucity and ambiguity of information regarding a partner's resources, capabilities and reliability (Gulati and Gargiulo, 1999), firms rely on different information sources for partner selection. In line with this, three perspectives have emerged in the literature until now, each emphasizing a different information source to come to a partner selection decision.

The first perspective suggests that organizations rely on directly observable characteristics ('nodal attributes') of prospective partners such as size, type of (business) activities and geographical location. The second perspective suggests that information is derived *through* the existing network structure. This perspective is called the embeddedness or social capital perspective. The third perspective, the 'network strategy perspective', states that organizations utilize knowledge and information *about* the network structure (Rowley and Baum, 2004; van Liere et al., 2008). Whereas each perspective carries validity in explaining partner selection choices, it remains to be explained when organizations use which of the three perspectives (nodal attributes, embeddedness and network strategy) when they select their partners?

To address this question, we introduce the notion of 'network accuracy': defined as the extent to which organizations know who is collaborating with whom, and who holds which position within the network structure. Previous studies assume that organizations have similar network accuracy. They either assume that organizations have a boundedly rational, myopic understanding of the network (Cook et al., 1983; Hite and Hesterly, 2001) or a complete understanding. The complete understanding is instrumental for strategically maneuvering and navigating the network, in line with the network strategy perspective (Skvoretz and Willer, 1993; Van de Ven, 1976; van Liere et al., 2008). In reality, however, the network accuracy of organizations differs widely (Knoben et al., in press; Lhuillery and Pfister, 2011). Nonetheless, the implications of this divergence in network accuracy remain unexplored.

To address this, we will advance and test the central claim that there is substantial heterogeneity in the network accuracy of organizations, and that this heterogeneity explains the use of different information sources, which leads to different partner selection choices. In short, we argue and show that when an organization has low network accuracy, it will rely on nodal attribute information and select homophilous partners. In contrast, when an organization has high network accuracy, it will rely on information *through* the

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network structure (following an embeddedness logic), and select structurally nearby partners. In case organizations rely on information *about* the network structure (following a network strategy perspective), they select strategic partners that are highly central or that enable them to bridge disconnected parts of the network structure.

The core contribution of this study is formed by its emphasis on organizational heterogeneity in network accuracy and its implications for partner selection choices. In this way, we contribute to two streams of literature. First, we contribute to the partner selection literature by specifically comparing the three theoretical partner selection perspectives in a coherent fashion, which have so far mainly been studied in isolation (Cummings and Holmberg, 2012). Studying the perspectives in isolation has limited our understanding about the relative validity of the perspectives. As a consequence, there has not been a systematic comparison of how these three perspectives, each emphasizing a different information source, result in different partner selection choices. We introduce the notion of network accuracy and show how it serves as a key boundary condition for the use of different information sources as well as how it carries consequences for different partner selection choices. The fact that, within a single network, different organizations use different sources of information for their partner selection has profound implications for our understanding of network behavior (Lumineau & Oliviera, forthcoming). It can help, for example, to understand the formation of bridging ties (Baum et al., 2005; Rosenkopf and Padula, 2008) or the formation of status-heterophilous ties (Collet and Philippe, 2014).

Second, even though we do not study the temporal developments in network structures, our study does make a contribution to the literature on network evolution. The link between our study and that literature lies in the fact that the evolution of a network structure is driven by the aggregated effect of partner selection choices by the organizations in it. So far, research has tried to explain network evolution by assuming that organizations all rely on the same partner selection logic. Some argue that network evolution is driven by organizations that try to position themselves strategically in the network structure (Rosenkopf and Padula, 2008), whereas others argue that network evolution can be explained by the use of simple heuristics that do not take the network structure into consideration. For example, organizations would select partners based on their size and neglect the network structure (Baum et al., 2010). By showing that organizations in the same network use different partner selection logics, and in which shares these partnering logics are used, we challenge an important assumption with regard to the micro-processes underlying the evolution of networks. Specifically, our findings imply that research on network evolution needs to consider inter-organizational networks as a setting in which some actors act strategically on the basis of the network structure amidst a group of other organizations that follow more naïve strategies.

Theory and hypotheses

Network accuracy

An organization's network accuracy refers to the degree to which an organization has a correct understanding of the relations present and absent between the other organizations in the network, as well as a correct understanding of which organizations hold which positions within the network structure. More specifically, it is commonly defined as the overlap between the network structure as perceived by organizations and the objective network structure (Krackhardt, 1990). Interest in network accuracy arose relatively recently and was based on the fact that the structures of (inter-organizational) networks are often extremely complex, comprising large numbers of relations and nodes, which makes accurate mapping cognitively difficult, costly and prone to errors (Lhuillery and Pfister, 2011). For example, earlier research showed that, even when a network is relatively small (about 20 nodes), individuals do not have accurate information about its structure (Kilduff et al., 2008) and some individuals make more accurate network assessments than others (Bondonio, 1998; Brands, 2013; Casciaro, 1998). Network accuracy is important, as it may support organizations in making a more fine-grained assessment of both opportunities and risks of collaborating with certain partners (Hahl et al., 2016). There is, however, a dearth of research that assesses network accuracy in inter-organizational settings and specifically of research that assesses the implications of differences in network accuracy for critical network behavior such as partner selection choices.

Below we will discuss three perspectives on partner selection decisions and argue that each perspective carries different (implicit) assumptions regarding the role of organizations' network accuracy. In addition, the three perspectives remain silent about the different implications for partner selection choices resulting from differences in network accuracy.

Low(er) network accuracy: information on nodal attributes

A low degree of network accuracy implies that an organization has a (very) limited understanding of the network structure and who is connected and/or disconnected to whom. This induces a need to rely on nodal attribute information, as this will form the only information available to assess a prospective partner's attractiveness. Information on nodal attributes is formed by easily observable partner characteristics, such as geographical proximity (Felzensztein et al., 2010) and the degree of similarity in organizational activities (Phene and Tallman, 2014). These form relatively simple informational cues to assess the degree to which a prospective partner is similar or homophilous, and hence attractive. As shown in earlier studies regarding reliability and trustworthiness, organizational homophily plays a key role in partner selection (Powell et al., 2005). Following this idea of homophily, actors tend to form connections with those who they consider similar, which instills ex-ante trustworthiness (McPherson et al., 2001) and mitigates risks of conflicts during collaboration (Rivera et al., 2010). Therefore, to the extent that organizations are more similar, they will consider each other more trustworthy and reliable and, therefore, more attractive for collaboration. A first proxy for easily and quickly assessing the degree of similarity with a prospective partner is formed by the nature of its activities. To the extent that a prospective partner is in the same business, it becomes more attractive as a future partner (McPherson et al., 2001; Rivera et al., 2010).

A second proxy for similarity that is easy to obtain is formed by the geographical proximity of a prospective partner (Felzensztein et al., 2010). Geographical proximity is commonly defined as the inverse of the geographical distance separating two organizations (Audretsch, 2003). Geographical proximity between two organizations could be important for partner selection for three reasons. First, geographical proximity implies a shared (regional) culture and shared values between organizations (Gertler, 1995). Shared culture and values facilitate mutual trust and act as a lubricant for inter-organizational interaction (Romanelli and Khessina, 2005). As a result, organizations are likely to judge nearby others as more reliable and trustworthy, which increases the likelihood of partner selection. In addition, organizations pay more attention to others that are geographically close (Bouquet and Birkinshaw, 2008), as geographic proximity enhances mutual visibility that in turn increases the likelihood of partner selection. Finally, given that geographical proximity is often argued to facilitate communication and information exchange (Knoben and Oerlemans, 2006), geographically proximate collaborations are often more effective and efficient (Weterings and Ponds, 2009), which is likely to result in a preference for such collaborations (Reuer and Lahiri, 2014). Hence, a more geographically proximate organization is a more attractive future partner (McPherson et al., 2001).

A last informational cue that is relatively easy to observe as well as to verify when network accuracy is low, is organizational size (Shipilov et al., 2006). Size may signal a partner's competence, as it serves as a proxy for past performance or the quality of resources (Chandler et al., 2013; Levinthal, 1991). The larger the organization, the more tangible and intangible resources it possesses, such as financial resources, legitimacy, and goodwill (Baum, 1999). This suggest that the larger a prospective partner, the more attractive it becomes as a future partner.

Overall, this suggests that when network accuracy is low, organizations will especially select those partners to which they are similar, based on both geographical proximity and similarity of activities, as well as organizational size. This leads to our first Hypothesis:

Hypothesis 1. The level of an organization's network accuracy will negatively moderate the effect of nodal attributes (i.e. homophily) on the likelihood of partner selection.

High(er) network accuracy: information on partner's network attributes

Information through the network structure: indirect ties

As we argued above, the key problem organizations face when selecting a new partner is the uncertainty surrounding its resources, capabilities, trustworthiness and cooperativeness (Gulati, 1995). To address this, the network embeddedness or social capital perspective suggests relying on an existing network structure that serves as a key source of information on the availability, competences and trustworthiness of potential partners. This information supports organizations in lowering the uncertainty that comes with external collaboration and partner selection decisions. So, organizations can rely on a network structure to access information that lowers search costs and aids organizations in their partner selection decisions.

Following this social capital perspective, information on these key partner characteristics arrives at the focal organization *through* the network structure, from referrals by trusted third-parties (structural embeddedness) and will typically be information about local partners (within maximum two-step reach). Such indirect ties may be brought to their attention by a common partner if there is a commonality in interests or complementarities in knowledge between a focal organization and an indirect tie. Here, a common partner - connecting the focal organization and the prospective partner - can offer referrals that reduce up-front uncertainty for a focal organization regarding both the competences and the trustworthiness of the prospective partner. Ex-post it can also receive information from the focal organization in case the partner misbehaves. So, indirect ties form attractive collaboration partners through the transitivity of trust and referrals by a common partner (Granovetter, 1985). To the extent that an organization's network accuracy increases and indicates that a prospective partner forms an indirect tie, the more attractive it becomes as a future partner. Hence, when an organization's network accuracy increases it will move away from using nodal attributes to select partners and rely on the finer grained embeddedness-based information obtained through the network instead.[1]

Hypothesis 2. The level of an organization's network accuracy will positively moderate the effect of information through the network structure (structural embeddedness, i.e. indirect ties) on the likelihood of partner selection.

Information about the network structure: network strategy

Following a network strategy perspective, relevant information for partner selection will be based on a network map, specifying who is connected and disconnected to whom. Information about the network structure implies information both about local partners and about distant partners, and what the beneficial positions within it are in order to maneuver into those attractive positions (Baum and Rowley, 2008). In this regard, it has been suggested that organizations are 'navigating' the network (van Liere et al., 2008).

According to this partnering logic, an organization will base its partner selection decision on the extent to which a prospective

[1] Relational embeddedness forms a dyad-level partner selection mechanism that is independent of the level of network information accuracy of the focal organization. This is why we do not hypothesize on relational embeddedness in this study. The same applies for the positional embeddedness of the focal organization. Even though this is likely to impact on partner selection choices, this effect will not be moderated by the degree of network information accuracy. Of course, both concepts are included in our analyses in the form of control variables.

partner ‘improves’ the organization's structural position in the network and will provide it with access to valuable resources held by the prospective partner (Hughes-Morgan and Yao, 2016). This suggests that when its network accuracy increases, an organization will rely less on nodal attribute information. Instead, it will rely on information about the larger network structure - its network map - that provides it with information on the attractiveness of a prospective partner. To explicate this further, we discuss how organizations engage in selecting partners based on their network map, and we distinguish between prominent partners and opportunities for bridging.

Partner prominence

The network strategy perspective points to the attractiveness of selecting partners that already have many ties. When an organization's map of the network structure indicates that a prospective partner occupies a central position, this is indicative of a prominent partner. Linking to such a partner is attractive for two reasons.

First, a central position signals visibility, status and hence attractiveness and, therefore, an organization tends to preferentially attach to the most central organizations in the network (Podolny and Stuart, 1995). Second, by linking to a highly prominent partner, an organization immediately positions itself in at least the semi-periphery of the network structure and can get access to potentially many indirect ties, through collaboration with a single new partner (Burt, 2007). In this way, it gets (indirect) access to a wide variety of resources in a very efficient way (Ahuja, 2000). So, by collaborating with a prominent partner, a focal organization can put itself into a highly beneficial position at relatively little costs (Rowley and Baum, 2008).

Clearly these mechanisms can only operate if the focal organization is aware of the fact which other organizations are central in the network. This suggests that to the extent an organization's network accuracy increases, and indicates that a prospective partner is prominently located in the network, the more attractive this organization becomes as a future partner.

Bridging

An embeddedness logic, emphasizing the role of information about local partners within a two-step reach, will miss out on information about distant partners, beyond a two-step reach. From a network strategy perspective, however, collaborating with a distant partner can be attractive. It may offer a focal organization the opportunity for bridging across disconnected ‘regions’ of the network structure (Muller-Seitz and Sydow, 2012). Bridging enables it to pursue attractive opportunities formed by access to new information, technology, resources and so on (Gilsing et al., 2008; Rosenkopf and Padula, 2008). In addition, bridging disconnected network regions may also enable an organization to control information and resource flows between different regions of the network (Burt, 1992; Hahl et al., 2016; McEvily and Zaheer, 1999), yielding power. This implies that, following the network strategy perspective, partners who increase an organization's bridging position may be considered attractive (Hagedoorn et al., 2011; Rowley et al., 2000; Soda et al., 2004).

Overall, this suggests that when an organization's network accuracy increases and an organization finds out a prospective partner is disconnected, this prospective partner becomes more attractive as a future partner. Based on this reasoning our third Hypothesis is:

Hypothesis 3a. The level of an organization's network accuracy will positively moderate the effect of information about the network structure (network strategy) on the likelihood of partner selection.

From the above, it follows that an organization's network accuracy forms a key boundary condition for the degree to which the organization will rely on different information sources for partner selection and, as such, will make different partner selection decisions. When an organization's network accuracy is low, information on nodal attributes will have a large influence on partner selection and organizations will mostly select homophilous or large partners. When an organization's network accuracy increases, the organization will rely less on coarse-grained information about nodal attributes and will rely more on fine-grained information through the network structure. As a result it will select mostly structurally nearby partners. For these structural embeddedness mechanisms to operate, network accuracy does not need to be at a very high level. Instead, network accuracy at a medium level, defined as an understanding of an organization's ‘extended network neighborhood’ (i.e. ties within a two-step reach), will already allow an organization to receive reliable information through the network structure.

In case its network accuracy increases, an organization will move away from information through the network structure (network embeddedness) towards information about the network structure (network strategy) and select strategically attractive partners. As a consequence, a higher level of network accuracy implies that an organization will rely on more sophisticated network structural information about prospective partners and hence will move away from embeddedness-based information and satisficing to strategizing in its partner selection decisions. This leads to our final Hypothesis:

Hypothesis 3b. The moderation effect of network accuracy will be stronger for information about the network structure (network strategy) as compared to information through the network structure (embeddedness).

Fig. 1 shows our core logic and visualizes our three hypotheses.

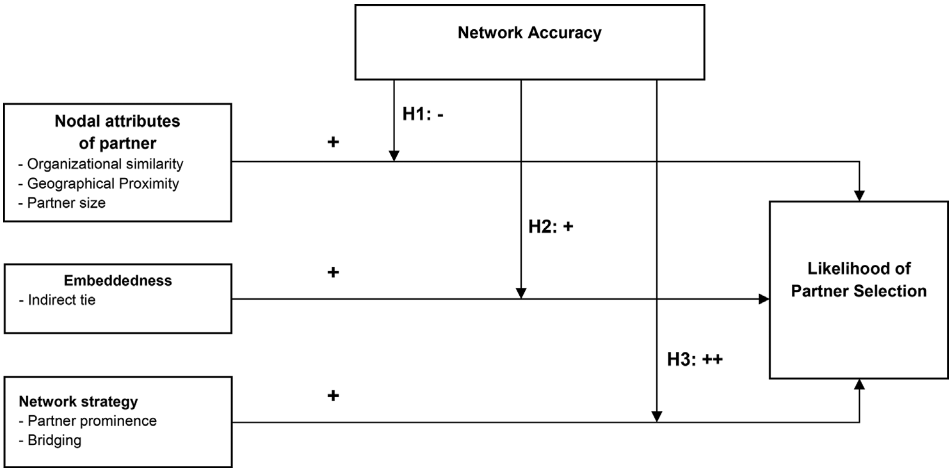

Fig. 1. Overview of hypotheses.

Methods

Data[2]

To test our hypotheses, we gathered data from two regionally bounded networks in the non-profit health care industry in the Netherlands in 2011. These networks are both part of a national platform that has two main formal goals: an internally-oriented goal and an externally-oriented goal. Externally, the aim of these networks is to speak with one voice to actors outside the network and to lobby for funding, mainly from local governments. Lobbying for funding is especially important, because Dutch austerity plans have put heavy pressure on government funding (Cylus et al., 2012). Internally, the goal of these networks is to stimulate cooperation and knowledge exchange among network member organizations in the non-profit health care industry, which make extensive use of volunteers for their daily operations. Cooperation among network members stimulates more efficient use of knowledge by sharing experiences about how previous activities were organized. Knowledge about how to recruit and retain volunteers is also essential to these organizations since in the Netherlands, dependence of non-profits on volunteers is increasing due to cutbacks in funding and the rise of what the Dutch government calls a 'participation society'. At the same time, the number of volunteers is declining (Dekker and de Hart, 2009). This creates a significant level of competition within the sector for this valuable and scarce resource. The implication for our study is a relevant one, as these organizations are faced with both the benefits of collaboration (knowledge about and access to volunteers) and the potential risks, such as a partner that might take away the volunteers that you recruited yourself. The implication for these organizations is that they need to be careful with whom to collaborate as well as to whom partners are connected. This puts a premium on network accuracy, making these networks valuable for our research purposes.

The national platform consists of 11 regional networks spread across the country. We selected two specific networks that had characteristics that make them especially suitable for our research purposes. First, unlike many other types of inter-organizational networks, these networks have clearly defined boundaries by virtue of the fact that membership of these networks is registered. Thus, they represent whole networks (Provan et al., 2007). Even though members join and leave over time, all network members at a particular point in time can be identified. This is a very important characteristic, as we need to ask all network members about their perception of the relation between every other pair of organizations in the network. This is almost impossible to do if the boundaries of the network are difficult to establish or if network involvement is purely serendipitous.

Second, the two networks selected for our study are medium sized (35 and 31 members respectively). For large networks, asking all network members about their knowledge of the relationship between every other pair of organizations in the network would be unfeasible, because the number of potential network pairs increases exponentially with the number of network members. Conversely, collecting data from small networks, while not problematic from a methods perspective, would not be especially interesting or informative due to a lack of network complexity. While we make no claim that our two networks are the "correct" size for the type of research we are undertaking, the size of the networks is well above the level at which Kilduff et al. (2008) found large distortions in the network information accuracy (20 nodes), but is at the same time not so large that data collection would be highly problematic.

We gained access to these networks through the chairperson of the national platform who endorsed the research and brought us into contact with the regional coordinators of the two selected networks. Both networks have meetings in which *fixed* representatives from the organizations come together to discuss matters related to the network. Those attending the meetings can be regarded as the most knowledgeable agents of the organizations for the purpose of our research. We attended one of these meetings for each network for our data collection. Before the meeting, the organizational representatives were informed that researchers were going to attend

[2] The data described in this paragraph is also used in Knoben et al. (in press). The description of the data collection process is therefore similar to the one in that paper.

the meeting by including the item on the meeting's agenda. However, they were not told what the content or goal of the research was. We provided a short introduction about how to complete the questionnaire and subsequently handed it out. We remained present to answer any questions. Some organizations completed the questionnaire during or immediately after the meeting but most opted to take the questionnaire with them, in which case we provided them with a return envelope. The few organizations that did not attend the meeting received the questionnaire by mail. After several rounds of e-mail reminders (starting after one week), a round of telephone reminders, and a few calls by the network coordinators and the platform chairperson (after approximately three weeks) the response rates ultimately were 97% for network 1 and 100% for network 2. The one non-respondent was a small organization whose representative was seriously ill. Analyses of the responses of the other organizations indicated that the missing organization was not perceived as very central in the network. We therefore concluded that omitting it would not influence our results. Ultimately, we had 34 respondents for network 1 and 31 for network 2. It should be noted, however, that because our unit of analysis is directed organizational pairs, this corresponds to $34 \times 33 = 1122$ observations in network 1 and $31 \times 30 = 930$ observations in network 2.

Measures

Partner selection

In this study we consider the partner selection decision from the perspective of a focal organization. Hence, we do not take a dyadic perspective that is common in studies on ´tie formation' as this requires *two* organizations to select each other in order to form a tie for future collaboration (Gulati, 1995; Li et al., 2008). As partnering preferences are not necessarily symmetrical among organizations (Mindruta et al., 2016), we use the focal organization's preferences of whom to form a new collaboration with as a more appropriate conceptualization of an organization's partner selection decision. Depending on the preferences of the prospective partners and the negotiation process between the two organizations, the partner selection decision could subsequently result in tie formation, but this is by no means a given (Mindruta et al., 2016).

To measure our dependent variable, we presented each network member with a list of all other network members, and asked the network members with which organizations it wants to form a new collaboration in the future. If the focal organization indicated this intention for a particular potential partner the dependent variable was coded ‘1’ and ‘0’ otherwise.

Nodal attributes. *Organizational similarity* was measured by establishing whether the focal and the assessed organization were active in the same sub-field of the healthcare industry. This information was obtained from the description of the organizations on their own websites. In cases where the website indicated multiple sub-fields, we categorized the organization based on the primary sub-field listed. Six sub-fields were distinguished: 1) psychiatric care, 2) physical disability care, 3) mental disability care, 4) aid for needy people (e.g. homeless people and asylum seekers) 5) social support (e.g. anonymous phone counseling), and 6) volunteer coordination. When both the focal and the assessed organization were in the same sub-field, *organizational similarity* was coded ‘1.’ All other cases were coded as ‘0.’

The measure of *geographical proximity* between the focal and the assessed organization was based on the geographical distance, measured in kilometers, between them. We did not obtain this information from the respondents but used the address information of their organizations and calculated these distances with an online travel planner. Since the decay of interaction and knowledge exchange due to geographical distance is commonly argued to be exponential instead of linear (Bode, 2004), we computed the natural logarithm of the shortest travel distance.[3] For our final measure of proximity, the scores were reversed.

Finally, the *size of the potential partner* is measured as the natural logarithm of the total number of employees (both paid and volunteers) of the potential partner.

Network Attributes - Embeddedness. To obtain the required network data, we started by identifying the ties of each focal organization. Respondents were given a list of all other organizations in the network and were asked to indicate with whom they shared knowledge. On the basis of these data, we compiled a locally aggregated structure (LAS) as a proxy of the objective network (identical to: Krackhardt, 1990). In this LAS, a knowledge exchange tie is present if organization ‘i’ reports exchanging knowledge with organization ‘j’, and vice versa. By aggregating the LAS of all nodes, the overall objective network was created.

On the basis of the network created by the LAS-procedure, all network attribute variables were calculated. The *‘indirect tie*’ variable takes the value ‘1’ when a potential partner has an indirect tie with a focal organization and ‘0’ otherwise and serves as our measure for structural embeddedness.

Network Attributes – Network Strategy. On the basis of the network data collected as described in the above we also computed the network strategy variables. The ‘*partner prominence*’ variable takes the value of the number of ties the potential partner has in the network (i.e. its degree centrality) (Moran, 2005).

Finally, *bridging* across disconnected regions of the network is measured as the change in the betweenness centrality of the focal firm if it would form a tie with the potential partner. Higher levels of betweenness centrality indicate that nodes occupy a position in-between otherwise unconnected parts of the network (Gilsing et al., 2008). As such, increases in betweenness centrality of the focal as a result of forming a tie with an alter imply that the alter currently is very disconnected from the focal organization and that a new

[3] Please note that we also constructed a version of this variable in which we use a linear distance decay function which yielded similar results in the subsequent analyses.

bridge in the network has been formed (McEvily and Zaheer, 1999). This measure is in line with others that have used increases in betweenness centrality as an indicator of the creation of shortcuts in the network (Rosenkopf and Padula, 2008) and of strategic network maneuvering (Muller-Seitz and Sydow, 2012).

Network accuracy. We also asked each organization about its perception of the existence of ties between all other organizations in the network. Instead of presenting focal organization respondents with a list of all possible pairs of organizations in the network, we presented them with a matrix containing the names of all organizations in the network (except their own) in the rows and columns. We asked each respondent to put the letter 'x' or a '1' in each cell where, to their perception, a knowledge exchange relation was present. As these knowledge exchange ties are undirected, we blackened half of the matrix and explained why this was done. Filling in this matrix was quite a difficult and labor-intensive task, which is why we were present during the data collection to answer questions the respondents might have.

The construction of the *network accuracy* variable was based on a comparison of the focal organization's perception of the network with the network resulting from the LAS-procedure reported above. In such a comparison, every pair of organizations can be classified in a two by two table (see table below). A tie can exist between organizations and the focal organization accurately perceives this (cell d) or it can believe that the two organizations are unconnected (cell b). Alternatively, a tie does not exist between the organizations and the focal organization perceives this correctly (cell a) or it believes that a tie does exist (cell c).

		Objective relation between organizations 'i' and 'j'	
		Absent	***Present***
Perception of organization 'k' of relation between organization 'i' and 'j'	***Absent***	***a***	***b***
	Present	***c***	***d***

On the basis of this information, numerous measures of association between perceived and objective assessments of network ties are possible (Krackhardt, 1990). Following a review by Gower and Legendre (1986) of 15 possible measures that capture the correspondence in such 2 × 2 tables, Krackhardt (1990) opted to use a measure called 's14'. This measure was chosen for its high resolution (appropriate sensitivity to small changes in correspondence) and low nonlinearity (low distortion at extreme values). Based on the same arguments we also opted to use this measure as our indicator of network accuracy. Mathematically, our measure takes the following form:

$$Network\ Accuracy\ = \frac{ad - bc}{\sqrt{(a + c)(b + d)(a + b)(c + d)}}$$

Control variables. We control for several characteristics of both the focal and alter organizations. First, *perceived resource value of the partner* was measured by asking each organization which other organizations possessed the most valuable knowledge regarding the recruitment and retention of volunteers (max 5 organizations could be selected). If the focal organization selected the potential partner as possessing such valuable knowledge, the variable took the value '1' and '0' otherwise. This type of question shows some similarities with the question used to measure the dependent variable. To prevent common methods bias from creating a spurious relation between these two questions (Podsakoff et al., 2003), we measure this variable with a slight time-lag, i.e. at a later meeting of the same network representatives. Unfortunately, not all respondents answered this question (i.e. we obtained response rates of 74% and 84%). Non-response analyses revealed no significant differences between the respondents and the non-respondents. Nonetheless, to prevent any potential bias of the non-response on this one measurement, we performed all statistical analyses separately with and without this particular variable and found no differences in the effects of the other variables. We therefore only report the models in which this variable has been included.

Second, we control for the perceived *resource value of the focal organization*, i.e. the value of the resources of the focal organization as perceived by the other organizations in the network. It is important to include this as a control as it may influence an organization's partner selection choices. An organization with valuable resources, especially in the eyes of potential partners, runs a higher risk of alters who seek collaboration in order to benefit from these resources and who become tempted to engage in acts of free-ridership. As a consequence, to the extent that a focal organization has valuable resources, it may become more selective in its partner selection choices and rely on different information sources when compared with organizations that have low (er) value resources. We measure this control variable using the same information as discussed above but now aggregated this information to the organizational level. Specifically, we calculate a variable that captures the percentage of other organizations in the network that name the focal organization as having the most valuable resources regarding the recruitment and retention of volunteers (Bothner et al., 2012).

Third, we control for organizational *size of the focal organization* by taking the natural log of the number of employees (paid and volunteers). Larger organizations have more people and resources at their disposal and, thus, can initiate and maintain more knowledge exchange relations. By controlling for the size of the focal organization we filter out such a pure scale effect.

Fourth, we control for whether the organization (both focal and potential partner separately) is a *subsidiary* or local branch of a larger national organization (obtained from their website). Subsidiaries of local branches might be less dependent on locally obtained knowledge, drawing instead on their parent organization's knowledge and experience.

Fifth, we included two control variables that capture whether the organization (both for the focal and the potential partner organization separately) has an explicit *religious organizational mission* statement (obtained from their website). The inclusion of this control variable is based on the observation that both networks contained what seemed to be a clique of organizations with explicit religious missions, whose members might be inclined to interact mainly with each other.

Sixth, focal organizations could select all organizations in the network as organization they would like to initiate new partnership with. They could therefore also select organizations they were, at the moment of the survey, already directly connected to. This would either boil down to a new tie (i.e. a repeated tie) or a second tie with the same partner (i.e. tie multiplexity). In any case, the existence of such a *prior tie* (i.e. relational embeddedness) is important to control for in our statistical models (Meuleman et al., 2010).

Finally, we control for the *degree centrality of the focal organization*. Doing so is important for two reasons. First, a high degree centrality could indicate a general willingness and ability to form (new) ties. Or, conversely, a high degree centrality could indicate that the organization has already reached its maximum capacity of ties it can maintain. In any case, it could influence its selection of new partners, which makes it important to control for. Second, it is argued in the literature that more embedded organizations (i.e. those with a higher degree centrality; positional embeddedness) have more information about what is going on in the network (Gnyawali and Madhavan, 2001). Degree centrality in this sense proxies for the extent to which the focal organization is a connecter and/or gatekeeper. In any case, a firm's degree centrality could be systematically related to its degree of network accuracy as well. Not controlling for it could, therefore, systematically bias the relationship between network accuracy and partner selection decisions.

Statistical analyses

Our dependent variable has a discrete distribution with the value of '1′ when the focal organization intended to form a tie with the potential partner, and '0′ otherwise. Following this distribution, we employed logistic regression analysis. A complicating factor, however, is that, as with all true network data, the observations are not independent. Each organization features multiple times in the datasets, both as a focal organization and as a (potential) partner, thereby creating dependence between observations. Moreover, the observations are not hierarchically nested, as is the case in a multilevel model. To correct for both dependencies at the same time, we used a multi-way clustering variance estimator developed by Cameron et al. (2011). This variance estimator is an extension of the standard cluster-robust variance estimator present in most statistical packages, but corrects for clustering of the standard error along multiple dimensions simultaneously. We use improvement of overall model fit based on log-likelihood ratio tests to identify the appropriate model for Hypothesis tests (Long and Freese, 2006).[4]

Our hypotheses propose moderation effects and the conventional way of testing such effects is through the inclusion of interaction terms in the regression models. A complicating factor in this regard, however, is that we propose moderation of six direct effects by the same moderator (i.e. network accuracy). This often results in multicollinearity problems and difficulties with identifying effects. To remedy such problems a split sample design is often proposed (Gelman and Park, 2009). This implies cutting the total sample into two or more groups based on scores on the moderating variable. Clearly, doing so implies a loss of power due to a reduction of the size of the sample. Moreover, setting the cut-off points for the different groups can be difficult. In an effort to get the best of both worlds, we utilize both methods. We first perform a split-sample approach in which we divide our total sample into three groups[5]; low, medium, and high network accuracy. Subsequently, we perform a full-sample analysis in which we include interaction effects. Assessing the similarities and differences between both approaches allows us to scrutinize the robustness of our results.

Results

The descriptive statistics and bivariate correlations for all of our variables are presented in Table 1. All correlations are well within acceptable bounds from a multicollinearity perspective. Given that our analyses largely rely on differences between organizations in their degree of network accuracy, Table 1 also contains the descriptive statistics for the three groups resulting from the sample split procedure mention above. Comparing the three groups actually shows that the groups are surprisingly similar on many variables such as size, subsidiary status and religiosity. However, three important differences do stand out. The higher degree of network accuracy, the *lower* the organization's perceived resource value, the *less* ties it has (reflected in lower scores on the ‘prior ties’ variables) and the *less likely* it is to form new ties (reflected in lower scores for the ‘partner selection’ variable). For these variables, the differences between the groups are statistically highly significant (all p-values < 0.01). This is a very interesting finding for two reasons. First, it shows that our key claim made in the beginning of this paper is a valid one in that there is a large degree of heterogeneity across organizations in their network accuracy. It indicates that both assumptions made in the literature until now - all organizations are myopic or all have the same perfect accuracy – are not realistic. Second, this finding suggests that the organizations with the most accurate network map are certainly not the most promiscuous. Instead, they are more reticent to form ties. If these different groups of organizations also rely on different informational cues to select partners, the combination of these findings could have important implications for network dynamics/evolution. We will get back to this issue in the discussion section of this paper.

The results of our split-sample logistic regressions are reported in Table 2. We estimated four models with model 1 being based on

[4] We first ran our models for the data from both networks separately and found nearly identical results. We subsequently ran a Chow-test (Chow, 1960), which also revealed that the relations between the independent variables and the dependent variable were statistically the same for both samples. Therefore, we decided to pool the data from both networks and only report the results for the pooled data. To control for any remaining differences between the two networks, we included a dummy variable at the network level.

[5] To assess the sensitivity of our findings to different group specifications we also estimated our models for two ways of splitting the sample in two groups; based on the median and based on the mean. In both instances we found results highly similar to the ones reported for the three group sample-split.

Table 1
Descriptive statistics and correlations.

Variable		Mean	Std.	VIF	Means of split samples on network accuracy			Bivariate correlations[a]				
					Lowest 1/3	Medium 1/3	Highest 1/3	1	2	3	4	5
1	Partner selection	0.27	0.45	–	0.34	0.26	0.21	–				
2	Size of the focal organization	2.37	2.15	1.26	2.46	2.40	2.23	0.04	–			
3	Subsidiary status focal organization	0.79	0.41	1.19	0.82	0.79	0.74	−0.14	−0.39	–		
4	Religious mission focal organization	0.10	0.30	1.13	0.10	0.10	0.09	0.07	−0.08	0.02	–	
5	Degree of the focal organization	6.85	5.57	1.77	7.35	6.45	6.70	0.18	−0.07	0.04	−0.26	–
6	Perceived resource value of focal	14.68	13.86	1.46	18.02	14.33	11.44	0.12	0.01	−0.01	0.01	−0.03
7	Perceived resource value of partner	0.13	0.34	1.21	0.16	0.13	0.11	0.09	−0.01	0.02	0.00	−0.01
8	Subsidiary status partner	0.74	0.44	1.27	0.74	0.77	0.70	0.02	0.01	−0.03	0.00	0.00
9	Religious mission partner	0.12	0.33	1.13	0.08	0.10	0.19	−0.04	−0.04	0.02	−0.02	0.05
10	Presence of prior tie	0.22	0.41	3.44	0.30	0.19	0.15	0.32	−0.02	0.01	−0.11	0.42
11	Organizational similarity	0.20	0.40	1.04	0.18	0.20	0.22	0.06	−0.03	0.04	0.03	−0.03
12	Geographical proximity	2.41	1.04	1.24	2.13	2.22	2.54	0.04	−0.08	0.07	0.04	−0.04
13	Size of partner	2.20	2.03	1.38	2.40	2.18	1.99	0.05	0.04	−0.02	−0.02	−0.07
14	Indirect tie	0.54	0.50	2.29	0.50	0.59	0.53	−0.14	−0.02	0.01	−0.02	−0.10
15	Degree of partner	6.02	5.20	1.70	8.44	6.25	3.21	0.17	−0.04	0.02	0.02	0.00
16	Δ Betweenness centrality	4.24	7.21	1.61	3.80	3.32	5.62	−0.08	0.00	0.01	−0.02	0.01
17	Network accuracy	0.62	0.25	1.21	0.37	0.67	0.85	−0.17	−0.02	0.02	−0.03	−0.09

Variable	Bivariate correlations[a]										
	6	7	8	9	10	11	12	13	14	15	16
1											
2											
3											
4											
5											
6	–										
7	0.39	–									
8	0.12	0.04	–								
9	−0.09	−0.03	−0.21	–							
10	0.16	0.16	0.02	−0.12	–						
11	0.08	0.03	0.00	0.05	0.11	–					
12	−0.09	−0.05	−0.04	0.05	−0.13	−0.04	–				

(continued on next page)

Table 1 (*continued*)

Variable	Bivariate correlations[a]										
	6	7	8	9	10	11	12	13	14	15	16
13	0.24	0.09	−0.33	−0.09	0.00	−0.03	−0.06	–			
14	−0.08	−0.09	−0.01	−0.03	−0.57	−0.09	0.14	−0.04	–		
15	0.34	0.13	0.07	−0.22	0.43	0.00	−0.09	−0.01	−0.05	–	
16	−0.05	−0.03	0.02	0.19	−0.31	−0.02	0.04	0.03	−0.20	−0.38	–
17	−0.25	−0.08	−0.03	0.15	−0.24	0.04	0.15	−0.06	0.02	−0.59	0.19

[a] N = 1605; correlations > (−).049 are significant at $p < .05$; > (−).065 are significant at $p < .01$; > (−).082 are significant at $p < .001$.

Table 2
Split-sample multiway-clustered logistic regression analyses.

Variables	Model 1		Model 2		Model 3		Model 4	
	Full sample		Low network accuracy		Intermediate network accuracy		High network accuracy	
Control variables								
Size of the focal organization	0.02	(0.03)	−0.03	(0.07)	−0.01	(0.11)	0.09	(0.13)
Subsidiary status focal organization	−0.98†	(0.53)	−0.57	(0.59)	−0.93	(0.62)	−1.57*	(0.64)
Religious mission focal organization	1.05	(0.72)	0.32	(0.76)	0.96	(0.69)	1.92*	(0.76)
Degree of the focal organization	0.02	(0.05)	0.06	(0.06)	−0.03	(0.06)	0.01	(0.06)
Perceived resource value of focal	0.01†	(0.00)	0.01*	(0.00)	−0.01	(0.01)	0.03*	(0.01)
Perceived resource value of partner	0.13	(0.22)	0.07	(0.32)	−0.37	(0.36)	0.92*	(0.42)
Subsidiary status partner	0.15	(0.08)	−0.02	(0.14)	0.65***	(0.19)	−0.41	(0.31)
Religious mission partner	0.12	(0.16)	−0.10	(0.35)	0.15	(0.46)	0.24	(0.27)
Presence of prior tie	1.84***	(0.59)	1.08	(0.82)	2.02***	(0.62)	2.77***	(0.75)
Network accuracy	−3.08*	(1.39)	−3.49**	(1.29)	−1.64	(2.86)	−1.76	(4.72)
Nodal attributes								
Organizational similarity	0.34	(0.22)	0.84**	(0.32)	0.01	(0.38)	0.06	(0.37)
Geographical proximity	0.28*	(0.14)	0.37*	(0.18)	0.19	(0.18)	0.15	(0.16)
Size of partner	0.07**	(0.03)	0.07†	(0.04)	0.18*	(0.07)	0.03	(0.05)
Embeddedness								
Indirect tie	0.42	(0.38)	−0.09	(0.57)	0.46	(0.50)	1.19***	(0.31)
Network strategy								
Degree of partner	0.03**	(0.01)	0.01	(0.03)	0.06**	(0.03)	0.16*	(0.07)
Δ Betweenness centrality	0.02	(0.02)	−0.03	(0.03)	0.01	(0.02)	0.08***	(0.02)
Network level fixed effect	Yes		Yes		Yes		Yes	
N	1605		563		515		527	
Log-likelihood	−790.10		−278.67		−257.44		−210.88	

a: Robust standard errors clustered at the focal organizational and the partner level are in parentheses.
†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

the full sample and models 2 through 4 each based on a third of the sample with the cutoff between the groups based on the scores for network accuracy. Supplementing these analyses, we also present the results of hierarchical regression analyses with interaction effects in Table 3. Model 5 from this table presents a baseline model with only the control variables in it. Model 6 adds the direct effects of the nodal attributes, the embeddedness and the network strategy variables. Models 7–9 consecutively add the interaction effects between these variables and network accuracy in three blocks, whereas model 10 includes all interaction effects simultaneously. As the split-sample approach and the interaction approach yield highly similar results, we will discuss the results based on the split-sample approach. In the few cases where the results differ we will discuss this explicitly.

Regarding Hypothesis 1, we indeed find strong evidence that organizations with a low network accuracy primarily rely on nodal attributes for their partner selection (see Table 2, model 2). For this group of organizations organizational similarity ($B = 0.84$, $p < 0.01$), geographical proximity ($B = 0.37$, $p < 0.05$) and partner size ($B = 0.07$, $p < 0.10$) all have a positive and statistically significant effect on the likelihood of partner selection.[6] To get more insight into the magnitude of these effects, we performed marginal effect analyses (Hoetker, 2007). These reveal that the sizes of these effects are also quite substantial. Being active in the same type of care activities, i.e. organizational similarity, increases the likelihood of partner selection from 31.8% to 46.4%. An increase in geographical proximity from 1 standard deviation below the mean to 1 standard deviation above the mean increases the likelihood of partner selection from 29.4% to 42.3%. The effect of partner size is the most modest in magnitude. Still, an increase in partner size from 1 standard deviation below the mean to 1 standard deviation above the mean increases the likelihood of partner selection from 30.8% to 37.1%. Moreover, the embeddedness and network strategy variables have very small, statistically insignificant effects in Model 2.

The findings based on the interaction models (Table 3) reveal highly similar findings. In model 7, we find negative and statistically significant interaction effects between organizational similarity and network accuracy ($B = -1.09$, $p < 0.05$) and geographical proximity and network accuracy ($B = -0.28$, $p < 0.01$). For partner size, we do not find a significant interaction effect which is caused by the fact that also for firms with intermediate levels of network accuracy partner size is a significant predictor of partner selection (Table 2, model 3, $B = 0.18$, $p < 0.05$). However, all in all, our findings strongly confirm Hypothesis 1.

The findings also present some support for Hypothesis 2. As network accuracy increases, the effect of indirect ties becomes larger, but it only becomes statistically significant in the group of organizations with high network accuracy (Table 2, model 4, $B = 1.19$, $p < 0.001$). For this group, marginal effect analyses reveal that having an indirect tie almost doubles the likelihood of partner

[6] The moderating effect of partner size does not become apparent from the models based on interaction effects (see Table 3). This is probably due to the fact that the importance of partner size first increases as the network accuracy increases (compare model 2 to model 3) and subsequently decreases (compare model 4 to model 2 and 3). In other words, the moderation seems to be non-linear which is why the interaction effect does not reflect it.

Table 3
Full sample multiway-clustered logistic regression analyses.

Variables	Model 5		Model 6		Model 7		Model 8		Model 9		Model 10	
Control variables												
Size of the focal organization	0.02	(0.03)	0.02	(0.03)	0.02	(0.09)	0.01	(0.09)	0.01	(0.09)	0.01	(0.03)
Subsidiary status focal organization	−0.95†	(0.55)	−0.98†	(0.53)	−1.01†	(0.53)	−0.96*	(0.53)	−0.99†	(0.53)	−1.02*	(0.53)
Religious mission focal organization	0.97	(0.76)	1.05	(0.72)	1.05	(0.71)	1.09	(0.69)	1.16†	(0.68)	1.16†	(0.67)
Degree of the focal organization	0.02	(0.05)	0.02	(0.05)	0.02	(0.05)	0.03	(0.05)	0.03	(0.05)	0.03	(0.05)
Perceived resource value of focal	0.01***	(0.00)	0.01†	(0.00)	0.01*	(0.00)	0.01†	(0.00)	0.01†	(0.00)	0.01	(0.00)
Perceived resource value of partner	0.12	(0.22)	0.13	(0.22)	0.13	(0.22)	0.13	(0.22)	0.13	(0.20)	0.12	(0.24)
Subsidiary status partner	0.02	(0.11)	0.15	(0.08)	0.12	(0.08)	0.13	(0.07)	0.14†	(0.07)	0.07	(0.13)
Religious mission partner	−0.04	(0.13)	0.12	(0.16)	0.13	(0.16)	0.09	(0.17)	0.14	(0.17)	0.10	(0.18)
Presence of prior tie	1.48***	(0.30)	1.84***	(0.59)	1.82***	(0.59)	1.88***	(0.59)	1.83***	(0.59)	1.83***	(0.59)
Network accuracy	−2.92*	(1.42)	−3.08*	(1.39)	−3.70*	(1.49)	−1.84*	(1.02)	−2.74**	(1.05)	−3.98***	(0.72)
Nodal attributes												
Organizational similarity			0.34	(0.22)	1.02**	(0.43)	0.34	(0.22)	0.34	(0.22)	0.76†	(0.42)
Geographical proximity			0.28*	(0.14)	0.47***	(0.18)	0.27*	(0.14)	0.29*	(0.15)	0.60***	(0.14)
Size of partner			0.07**	(0.03)	0.06*	(0.03)	0.06**	(0.03)	0.07**	(0.03)	0.02	(0.05)
Embeddedness												
Indirect tie			0.42	(0.38)	0.43	(0.39)	0.36	(0.47)	0.44	(0.38)	0.44	(0.36)
Network strategy												
Degree of partner			0.03**	(0.01)	0.04***	(0.01)	0.03**	(0.01)	−0.02	(0.02)	0.01	(0.02)
Δ Betweenness centrality			0.02	(0.02)	0.02	(0.02)	0.02	(0.02)	−0.02	(0.03)	−0.02	(0.03)
Interaction effects												
Organizational similarity* Network accuracy					−1.09*	(0.56)					−0.66	(0.72)
Geographical proximity* Network accuracy					−0.28**	(0.12)					−0.48***	(0.18)
Size of partner* Network accuracy					0.01	(0.08)					0.06	(0.09)
Indirect tie* Network accuracy							0.14	(0.47)			0.02	(0.46)
Degree of partner* Network accuracy									0.09***	(0.02)	0.05*	(0.02)
Δ Betweenness centrality* Network accuracy									0.06†	(0.03)	0.05†	(0.03)
Network level fixed effect	Yes		Yes		Yes		Yes		Yes		Yes	
N	1605		1605		1605		1605		1605		1605	
Log-likelihood	−807.15		−790.10		−788.06		−790.59		−787.39		−786.85	
ΔLog-likelihood	–		17.05**		19.09**		16.56**		19.76**		20.30***	

a: Robust standard errors clustered at the focal organizational and the partner level are in parentheses
†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

selection. Specifically, the likelihood increases from 15.6 to 28.9%.

However, this moderation effect is not present in the models that rely on interaction effects (Table 3, model 8 and 10). This is likely to be due to the non-linear nature of the moderation as showed by the sub-sample models and lends support to the point that the importance of indirect ties does not increase uniformly with increasing network accuracy. So even though our findings do not provide direct support for Hypothesis 2 (since moderation is only statistically significant for the high accuracy group of organizations), our results do show that indirect ties become an important predictor of partner selection once a threshold value of network accuracy (0.81 in our dataset) has been exceeded.

With regard to Hypothesis 3a, we do find strong evidence that as network accuracy increases, the likelihood of partner selection being based on network strategy information increases. For the degree centrality of the partner, we find that the effect becomes more pronounced as network accuracy increases (see Table 2). For organizations with the lowest network accuracy, the effect is statistically insignificant (model 2). For organizations with an intermediate accuracy (model 3, $B = 0.06$, $p < 0.01$), an increase in the degree centrality of the partner from 1 standard deviation below the mean to 1 standard deviation above the mean, augments the likelihood of partner selection from 21.3% to 30.7%. For organizations with the highest accuracy, however, the effect is even larger (model 4, $B = 0.16$, $p < 0.005$). For this group an increase in the degree of the partner from 1 standard deviation below the mean to 1 standard deviation above the mean augments the likelihood of partner selection from 16.1% to 45.8%; almost tripling the likelihood.

Furthermore, the bridging variable only has a positive and highly statistically significant effect for the group with the highest network accuracy (model 4, $B = 0.08$, $p < 0.001$). For this group an increase in the change of betweenness-centrality resulting from a partnering choice from 1 standard deviation below the mean to 1 standard deviation above the mean increases the likelihood of partner selection from 16.9% to 27.8%.

However, contrary to Hypothesis 3b, reliance on network strategy information does not seem to go at the expense of the reliance on embeddedness information. Instead, as network accuracy increases, the reliance on embeddedness *and* network strategy information seems to increase at the expense of relying on nodal attribute information. Moreover, the effect of indirect ties only becomes significant for the high network accuracy group, which contradicts hypothesis 3b. So all in all, our findings do not confirm hypothesis 3b. The reliance on network strategy information does increase with increases in network accuracy, but this effect is not stronger than the effect on the influence of embeddedness information obtained through the network.

Robustness tests

To test the robustness of our results, we ran two additional sets of analyses.[7] First, we used different formulas for the calculation of our network accuracy variable. We did so because our measurement does not allow us to differentiate between situations in which respondents do not know whether there is a partnership between two organizations or whether they really believe that there is no partnership. Given that most pairs of organizations do not have partnerships, an organization that knows very little about the network and therefore leaves the matrix largely empty would still have a moderately high accuracy score. To check whether this could have influenced our results we re-ran our analyses using different calculations of network accuracy. Specifically, we selected measures that ‘punish’ harder for using the answering strategy of under-reporting partnerships. In one measure we ‘punish’ respondents twice for errors of under-reporting existing partnerships and in the other alternative measure we only ‘punish’ for under-reporting but not for over-reporting.[8] These alternative accuracy measures correlate very highly ($r = 0.85$, $r = 0.92$) with our main accuracy measure indicating that the answering strategy of systematically under-reporting partnerships is not used frequently by our respondents. Moreover, re-running our analyses with these alternative measures provides identical results in terms of directions of effects and their statistical significance. All in all, these analyses show that our findings are very robust against the specific measurement of network accuracy.

Second, we test the robustness of our results against potential omitted variable bias by running our analyses including focal firm-level fixed effects. These fixed effects capture all (un)observed differences between focal firms and therefore make it impossible to include focal firm-level variables as controls, including an organization's level of network information accuracy. We could therefore apply this approach only to our split-sample estimations and not to the interaction-based models. The results of these analyses (available from the authors on request) are highly similar to those of the main analyses reported in the manuscript in terms of directions and significances of results. As such, we conclude that our findings are robust to potentially omitted variables.

Discussion & conclusions

In this study, we argued and showed that there is substantial heterogeneity across organizations in their network accuracy. This heterogeneity in accuracy gives rise to differences in sources of information about prospective partners used for partner selection. Overall, our findings indicate that an organization's network accuracy serves as an important moderator of the relationship between different informational cues and partner selection decisions. When organizations have low network accuracy, all they can do is rely on easy to observe and verifiable, factual information on nodal attributes. In line with this, they select homophilous partners in terms of business activities and geographical location, or they select large partners. When network accuracy increases, it attenuates this role of nodal attribute information as both organizational similarity and partner size lose their appeal as these form relatively crude sources of information. At the same time, we find that network accuracy strengthens the role of more fine-grained information sources formed by both embeddedness-based cues (information through the network) and network strategy cues (information about the network).

Theoretical contributions

These findings have important implications for the partner selection literature. Specifically, they advance our understanding of the extent to which organizations rely on different sources of information and how this impacts on their partner selection choices. We show that all three sources of information are relevant to explain partner selection by organizations. This implies that it is not so much which source of information is most important for partner selection choices as such, but instead that different information sources are used by organizations with different degrees of accuracy.

These main findings link well to another finding, namely that the perceived resource value of a prospective partner also becomes a significant predictor of partner selection when the network accuracy of an organization increases, whereas organizational size of the partner is no longer used. This shows that organizations with a high network accuracy rely on a more direct, perceptual measure of the value of their partners at the expense of a more coarse-grained proxy such as organizational size. This suggests that organizations with a high degree of network accuracy are able to assess a partner's trustworthiness based on its network attributes (e.g. does it form an indirect tie or does it have many direct partners?), as well as the value of a partner's resources. High network accuracy enables organizations to clearly consider ‘both sides of the same coin’, i.e. risks *and* benefits, and to move beyond a ‘simple’ nodal attribute approach or beyond a merely satisficing approach aimed at selecting ‘good enough’ partners. High network accuracy not only enables

[7] Besides these formal robustness tests we also explored the three-way interactions between combinations of information sources organizations can use for partner selection and network accuracy. Two main findings can be derived from these analyses: 1) they do not change our main results in any way, 2) the vast majority of the interactions are statistically insignificant. An exception to point 2 is formed by the interactions between geographical proximity and the embeddedness/network strategy variables. Here our findings are largely in-line with extant literature that suggests that geographical proximity complements other information sources as it aids communication and can help information travel (Ter Wal, 2014).

[8] Specifically, the formulas used are.$\mathrm{Accalt1} = \frac{\mathrm{a+d-(c+2b)}}{\mathrm{a+b+c+d}} Accalt2 = \frac{a+d-b}{a+b+c+d}$.

organizations to prevent the potential downside of collaboration but also to consider its upside by assessing a partner's attractiveness based on the value of the resources that it possesses.

Our findings also complement some recent studies on collaboration with distant or status-heterophilous ties. Baum et al. (2005) demonstrated that negative (economic) performance serves as a 'master switch' to collaborate with distant partners. Ahuja et al. (2009) showed that if the 'terms of trade' (i.e. getting a majority versus a minority stake in the alliance) are favorable enough for the central player it will get involved in collaborations with peripheral players. Whereas both studies emphasize the importance of a sound (economic) motivation to initiate such a distant and risky collaboration, our study shows that accomplishing such a collaboration comes with a partner selection decision that is enhanced by the ability to accurately perceive the network structure in terms of present and absent ties.[9] As this forms an important yet not straightforward task, as collaboration with such disconnected partners is risky and uncertain, organizations do not only rely on their network map but also on embeddedness-based information obtained though the network structure. This combined use of both information sources enables organizations to triangulate between them, and in this way to come to a better informed and more reliable partner selection choice. This explains then why the substitution of embeddedness-based information by network strategy information does not occur, contrary to our prediction in Hypothesis 3b, but that both information sources serve as necessary complements for high accuracy organizations, in order to make a better informed decision on their partner selection choice.

Moreover, given the degree of heterogeneity in information sources organizations use for partner selection, statistically, many dyads will be characterized by asymmetric use of information sources. This implies that the reasons why organizations decide to partner need not be the same for both parties. For example, organization A might like to partner with organization B because it is large (relying on nodal attribute information) whereas organization B wants to partner with organization A because it is very centrally positioned (relying on network strategy information). As such, single-perspective network studies, studies that only take into account the perspective of organization A or B, are unlikely to provide good explanations of network dynamics (Mindruta et al., 2016). As the field of inter-organizational network studies is still dominated by such single-perspective studies, there is ample room for extensions that take into account the perspectives of both parties involved in the collaboration (Lumineau & Oliviera, forthcoming). In this regard, our study shows that understanding how network structures change over time requires future studies to take into account the heterogeneity of information sources that organizations use for their partner selection decisions. Incorporating heterogeneity in information sources becomes even more salient when looking at multi-party collaborations where the potential for asymmetric information, preferences and goals are even higher than in dyads (Heidl et al., 2014).

These contributions to the partner selection literature, in turn, feed into a contribution to the network evolution literature. The link between our study and that literature lies in the fact that the evolution of a network structure is driven by the aggregated effect of partner selection choices by the organizations in it. In this regard, an implication of our study is that a large part of the change in network structures is driven by organizations using rather unsophisticated partner selection strategies. This follows from the fact that the organizations lowest in network accuracy and using the least sophisticated partner selection strategies are the most promiscuous (see Table 1). The more sophisticated the network strategy, the more reticent organizations become with regard to new tie formation. As a result, large parts of the change in network structures will result from organizations connecting to organizations that are similar to themselves or to organizations that are very visible due to their size. This can explain why the literature considers homophily as a dominant mechanism, simply by its power to explain the lion's share of formed collaborations. However, a small part of all partner selection decisions is based on structural network considerations such as connecting to indirect ties or maneuvering into bridging positions. This finding resonates with earlier studies that such partner selection decisions are rare (Baum et al., 2005) and that their value is 'not in their prevalence but in their scarcity' (Rosenkopf and Padula, 2008: 671). So, from a perspective of network change, this implies that a large part of the changes in network structure could be considered as 'noise'. These changes could simply be by-products of organizations selecting partners without considering the network (Baum et al., 2010; Ebbers and Wijnberg, 2010). In contrast, however, a small part of the network change is the result of organizations purposefully acting on the basis of structural network information and trying to maneuver into favorable network positions (Rosenkopf and Padula, 2008; Rowley and Baum, 2004). Whereas previous studies have (implicitly) assumed that organizations are homogenous regarding their network accuracy, either assuming a boundedly rational, myopic understanding that implies a homophily logic (Cook et al., 1983; Hite and Hesterly, 2001), or a complete understanding that is instrumental for strategically maneuvering and navigating the network (Skvoretz and Willer, 1993; Van de Ven, 1976; van Liere et al., 2008), there is in fact a large degree of heterogeneity in network accuracy. As such, we challenge an important assumption with regard to the micro-processes underlying the evolution of networks. All in all, our findings imply that research needs to consider inter-organizational networks as a setting in which some actors act strategically on the basis of the network structure amidst a group of other organizations following more naïve strategies.

Practical implications

Our findings also have important practical implications. As stated earlier, our research shows that partner selection processes are likely to be asymmetrical in the sense that the reasons why organizations decide to partner need not be the same for both parties. One party might decide this based on size or geographical proximity, whereas the other might base this decision on network structural

[9] In addition, in both studies the authors report that these types of collaboration are (very) scarce and exceptional, when compared with the total amount of ties formed in the network. This is in line with our earlier finding in our descriptive statistics that organizations with a high accuracy are much more selective in their partner selection choices as opposed to those with low accuracy.

consequences. From a managerial perspective, such asymmetries in partner selection logics are highly important to take into consideration when approaching potential partners. Characteristics that can make one attractive as a partner to some organizations do not work in one's favour for other organizations. As such, figuring out your prospective partner's partnering logic seems paramount to forming partnerships successfully.

Limitations and directions for future research

Even though our research makes a useful contribution to the network literature, and the partner selection literature specifically, several limitations also apply. First, our dependent variable is partner selection and not tie formation. We opted for this dependent variable as many of the theoretical arguments we wanted to test are inherently asymmetrical for the two parties involved. However, for exactly the same reason it is unclear how these, asymmetrical, partner selection preferences play out in terms of actual ties being formed. As such, a logical extension of our research would be to assess the tie formation process between organizations with, for example, different network maps.

Second, even though we selected our empirical setting with great care, we cannot exclude the possibility that the relative importance of the different information sources will differ between networks. Networks differ, for example, in size, degree of coordination, degree of goal alignment and the degree of competition and these differences will impact on which information sources organizations use to select partners. We selected medium sized networks with some goal alignment and coordination on the one hand, but also with some competition. As such, replications and extensions of our work in 'more extreme' networks would be valuable.

Third, our study does not establish a causal relation between the use of (different) information sources and partner selection. Specific forms of endogeneity could therefore be of influence on our results. Of specific relevance is the issue of reverse causality. It is possible, or perhaps even likely, that organizations that want to establish partnership with disconnected alters realize that they are in need of accurate network information in order to do so and start to gather such information. As such, our findings should be seen as associations rather than causations. This limitation raises interesting questions for future research with regard to how organizations search for network information, how costly it is to do so, and how successful those strategies are. It does not, however, invalidate our main findings that a) there is great heterogeneity in network strategies across organizations and b) that the utilization of those strategies is systematically related to differences in network information accuracy.

Fourth, and related to the above, our study provides no information on the mechanisms at play inside the organizations. How is network information processed and used in partner selection processes? In this regard a recent study by Deken et al. (in press) showed that resource complementarity is not determined before the partner selection decision but rather is constructed in an iterative way during the tie formation process. Similar studies on how embeddedness and network strategy is constructed and used in organizations will greatly help in understand the (causal) mechanisms at play during partner selection.

Finally, our study highlights that organizations differ in the level of sophistication of the information organizations use for their partner selection decisions. It is tempting to assume that utilizing more sophisticated information results in better decision making and, therefore, in superior performance. We would like to emphasize, however, that this need not be the case. It is an empirical question whether using and network strategy information and being very selective on whom you partner with is a winning strategy over relying on more easily obtainable nodal attribute information and being more promiscuous in terms of partner selection. Therefore, analyzing the performance differentials between organizations relying on different information sources for their partner selection seems a logical and valuable extension of our study.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.lrp.2018.06.001.

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