The Impact of Network Centrality on Related and Unrelated Knowledge Transfers in Alliances

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The formation of R&D alliances is a viable option for firms to supplement their in-house R&D and share the costs and risks inherent in innovations. Strategic R&D alliances promote knowledge transfers in alliance-related areas (intended knowledge transfers) that serve the common scope of the alliance, while also leading to spillovers of knowledge in alliance-unrelated areas, outside the scope of the alliance (unintended knowledge transfers). This paper looks at the social network of the partnering firms, in particular, network centrality which reveals the firm's position and status in its network. By partnering with other firms, firms can extend their access to resources and information, so the number of partners they have (the centrality of the firm) becomes important. We argue that network centrality promotes cooperation and thus increases the intended knowledge transfer. Furthermore, network centrality also predicts opportunistic behavior in alliances, reducing the transfer of unintended knowledge. The results support the predictions made.

Keywords: alliance, knowledge transfer, social networks

INTRODUCTION

Companies have adopted numerous alternatives to complement their in-house R&D as the costs and risks of innovation continue to grow. Forming R&D alliances is one such alternative. Research and development alliances provide partner firms with complementary knowledge (Teece, 1986; Ceccagnoli and Hicks, 2013; Jiang and Jiang 2019). It appears that R&D alliances are on the rise, particularly in technology-intensive industries.

Many studies have examined knowledge transfers, but few have examined distinct types of knowledge flows, despite continued interest in alliances as a method of knowledge acquisition. As Oxley and Wada (2009) note: "Extant empirical research on the scope of knowledge transfer is quite sparse, reflecting difficulties in accessing adequate data and devising measures of knowledge flows in different areas, something that bedevils all empirical work in knowledge management." According to Mowery, Oxley, and Silverman (1996), knowledge flows between alliance partners are measured by the increase in partner cross-citations after the alliance compared to before the alliance. They find that equity joint ventures enhance interfirm knowledge transfers compared to contract-based agreements when measuring knowledge flows in alliances using this measure. Using a similar measure, Gomes-Casseres, Hagedoorn, and Jaffe (2006) found that alliances facilitate more knowledge flow than non-allied firms while Ravichandran and Giura (2019) address the impact of information technology investments on knowledge flows. Using the same measure, Elia, Petruzzelli, and Piscitello (2019) address cultural diversity and state that innovation can be more problematic in multinational alliances involving subsidiaries.

These studies provide valuable insights and indicate substantial knowledge flows occur in alliances. Further, Oxley & Wada (2009) examine how knowledge flows are decomposed into two areas: knowledge flows in related areas of alliances and knowledge flows in unrelated areas of alliances. Due to their direct relevance to alliance activities, knowledge flows in alliance-related areas are likely to be the result of intentional transfers (Oxley and Wada, 2009). In contrast, knowledge flows in unrelated alliance areas are likely to be unintentional and the result of appropriation hazards and spillovers. Using this fine-grained measure, as compared with contract-based alliances, Oxley and Wada (2009) find that joint ventures promote knowledge transfer within alliances and reduce knowledge transfer outside of alliances. Following Oxley and Wada (2009), the purpose of this paper is to extend research on knowledge flows in alliance-related and alliance-unrelated areas and to examine the impact of a firm's network centrality on alliance-related and alliance-unrelated knowledge flows.

Firms rarely innovate in isolation, and they depend heavily on external partners to develop sustainable competitive advantages (Powell *et al.*, 1996). Due to the capabilities and access to the knowledge provided by the social network, alliances are considered to be the principal factors of firm innovation (Gulati, Nohria, & Zaheer, 2000). Based on the network perspective, the social network of external contacts is the most important aspect of an organizational environment, and the actions taken by the focal firms are influenced by this social environment in which they find themselves (Granovetter, 1985). A network structure can enhance a firm's ability to identify and develop opportunities when forming alliances. Links, referrals, and access are some of the advantages networks offer (Burt, 1992). Stuart (2000) argues that alliances are access relationships and that if the focal firm has a portfolio of technologically advanced strategic alliances, the firm will have higher post-alliance innovation rates. A firm's connections can provide timely access to knowledge and information. Additionally, referrals allow firms to bypass formal channels and gain access to information and knowledge faster. It is therefore undeniable that networks play a significant role in influencing alliance outcomes.

Researchers have long recognized the impact of social networks on innovation, and more recent studies have begun to explore how the position of a firm within a network impacts innovation outcomes. Direct and indirect ties can positively influence innovation, while structural holes can negatively impact it (Ahuja, 2000). In their 2007 article, Schilling and Phelps argue that firms with high reach in dense networks are more innovative than firms with low reach in low-density networks. The stability of the firm's ego-network composition affects the firm's innovation, mainly reducing innovation for the focal firm (Kumar and Zaheer 2019).

Examining knowledge transfers in alliances is incomplete without taking into consideration the firm's network position, especially its network centrality. Through the formation of new alliances and the maintenance of existing alliances, firms form a social network of direct and indirect ties. A firm's position in the network will influence its willingness to transfer technological capabilities within the alliance. Creating patterns of interaction within the social network can increase knowledge transfer (Burt, 1992). A firm's position within a network can influence the behavior of firms, and therefore the decisions they make regarding transferring technological capabilities within an alliance. The firms with higher centrality are both willing and able to share knowledge related to the scope of the alliance (alliance-related knowledge). These highly central firms have access to increased knowledge due to their high number of connections and thus have the ability to share knowledge with their partners. Further, while these firms have formed a high number of alliances, they have developed strong cooperation skills and high knowledge-sharing capabilities. Furthermore, these firms follow the norms imposed by the network, and they collaborate willingly.

Not only that alliances demand significant time and effort to find the right partners and to develop routines that support interaction, but they also behave differently to achieve their objectives and some may try to willfully extract knowledge with the intent to outlearn the partner (Hamel, 1991) thus behaving opportunistically. In this paper, I argue that network centrality prevents some of the opportunistic behavior and reduces the transfer of unintended knowledge (alliance-unrelated knowledge), while it promotes collaboration and thus increases the transfer of intended knowledge (alliance-related knowledge).

THEORY AND HYPOTHESIS

Alliances have been discussed extensively in literature as a source of value creation for partner firms (Anand & Khanna, 2000; Das, Sen, and Sengupta, 2003; Dyer, Kale, & Singh, 2001; Kale, Singh, & Perlmutter, 2000; Williamson, 1991). In an alliance, the partner firms will approach matters in innovative ways that are less likely to occur in each of the partners if no alliance is formed. According to the Resource Based View, firms are conceptualized as bundles of resources, a unique set of tangible and intangible assets (Penrose 1959). Rumelt (1984) argues that these resources give the firm its competitive advantage. RBV holds that the reason firms form alliances is to gain access to resources that would otherwise not be available to them and to generate new resources.

R&D alliances offer various advantages such as allowing firms to learn from their differences and complementarities, but they also carry costs and hazards such as the costs associated with coordination, and the risk of unintended knowledge transfers. Unintended knowledge transfers to the partner can be either in the form of leakage or in the form of appropriation of valuable technologies. As alliances are incomplete contracts between firms, they result in unintended knowledge flows. A contract cannot detail all the possible future interactions due to the bounded rationality of humans (Simon, 1947). Only the knowledge that serves the common scope of the alliance is meant to be transferred into the partnership. While cooperation is the main scope of the alliance, there is also competition between the partners as they might be operating in the same industry (Hamel, 1991). This competition has significant impacts on the dynamics of the learning process and creates tension. Contracts would be perfect if humans were rational rather than bounded rational, as they would specify all the possible ways in which a company would be able to obtain knowledge from its partner in an alliance. The unintended transfer of knowledge to the partner would not be an issue in the perfect contract world. However, as Williamson (1975) observes, perfect *contracts are impossible to write* and despite all efforts and costs, a contract does not fully specify what each party must do under every circumstance.

For an alliance to be successful, firms must find a balance between maintaining an open knowledge exchange and preventing knowledge leakage. According to Doz (1996), firms enter alliances with shared, explicit expectations, as well as less explicit, private expectations. When firms join forces, they know that there will be some unintended knowledge loss, but how much and how it will affect the success of the alliance and each firm afterward is unknown.

Trust among partners serves as a mechanism for achieving the right balance between protecting and sharing information. Thus, some of the alliance literature has emphasized the importance of trust alliances. Kale *et al.* (2000) propose the concept of relational capital, which they define as the level of mutual trust, respect, and friendship between alliance partners derived from their close personal interactions. It takes time for relationship capital to be built but building it positively influences the willingness to transfer knowledge in alliances. It is no surprise that relationship capital is related to alliance success, learning, and limiting the opportunism of partners (Kale *et al.*, 2000). When trust exists between partners, one can expect that opportunism by the other will be reduced.

In addition, communication increases the flow of intended knowledge in alliances. Alliance partners must interact frequently, not only formally but also informally, to achieve their goals and to transfer alliance-related knowledge. Increased interactions facilitate sharing of both tacit and explicit knowledge (Inkpen, 1998).

Since firms can extend their access to resources and information by partnering with other firms, the number of partners each firm has (the centrality of the firm) becomes important. Centrality, a measure of how embedded a firm is in its network, captures the firm's positional advantage and status within the network. Centrality implies a greater degree of access to information and resources (Burt, 1992) which leads to the idea that network centrality is a source of power. Centrality provides the focal firm with access to network resources that provide strategic opportunities, affect the firm's behavior and value (Lavie, 2007), shape alliance formation decision (Gulati, 1999) and enhance a firm's market performance. In this paper, centrality represents the total number of direct ties a firm has in its industry.

The centrality of the actors in the social network influences the actions that firms take (Granovetter, 1985). The centrality of a firm in a network can function as a resource, but it can also act as a constraint by enforcing norms of behavior among individuals or corporations (Walker *et al.*, 1997). These constraints in an alliance reduce opportunistic behavior and contribute to the success of the alliance. The knowledge transfer in alliance-related areas (intended knowledge transfers) will therefore be increased, the knowledge that otherwise would have been hindered by the expectation that the partner would behave opportunistically. As firms build their network and form alliances, and thus achieve higher centrality and gain experience in forming and managing partnerships, they become better at cooperating with their partners and better at facilitating alliance-related knowledge transfer. Collaboration experience helps firms recognize synergies in various types of alliances (Powell, Koput, & Smith-Doerr, 1996). We expect that firms with higher centrality will be able to share knowledge more easily and expose their partners to a wider variety of knowledge opportunities.

In a network, centrality promotes shared understanding and cooperation (Powell, Koput, & Smith-Doerr, 1996). The information that flows through a network is influenced by all actors in the network. Cooperation and competition are both part of the actors' relationships. Eliminating your competition might mean eliminating your partner in another project therefore is not an option. (Powell, Koput, & Smith-Doerr, 1996). Some norms have to be respected in the network and highly central firms respect these norms to maintain their centrality and are more willing to share knowledge expecting knowledge sharing in return from their ties. Thus, we expect alliance partners that have high centrality to learning most from each other in alliance-related areas. Based on the above arguments, we hypothesize that:

Hypothesis 1: *The centrality of the partners in the network has a positive impact on the transfer of intended knowledge flows.*

While firms rely on their partners to learn from a new alliance (Pfeffer & Salancik, 1978), they must also protect themselves from opportunistic behavior from those partners. Alliances are self-enforcing arrangements, and they imply a high level of mutual interdependence between partners, which makes them vulnerable to opportunism by one partner. If one party exhibits opportunistic behavior, the other party's recourse is to limit the interactions and thus limit the transfer of knowledge that is within the scope of the alliance or terminate the alliance. Since alliances are characterized by instability that arises from uncertainty concerning a partner's future behavior, successful cooperation cannot be achieved between the partners of an alliance without constraints on the partners to perform according to each other's expectations. Embeddedness theory acknowledges that "the ongoing networks of social relations between people discourage malfeasance" (Granovetter, 1985). Network formation is path dependent and the early partner choices have a significant impact on future collaborations (Walker *et al.*, 1997). Firms guide their choices based on past actions with other firms and continue to deal with those they trust. Better than the statement that someone is known to be reliable is information from a trusted informant that has dealt in the past with that firm and has found it to be so. There is undoubtedly a preference for transacting with firms of known reputation. One incentive not to cheat is the cost of damage to one's reputation (Granovetter, 1985). Relational capital, which is important in alliances (Kale *et al.*, 2000) plays a significant role in the context of network structure.

The ability of a firm to form new relationships depends on its position in the prior network structure (Ahuja, 2000). In order words, a firm not only has to want to ally, but it also must be attractive to potential partners. Finding a trustworthy alliance partner requires access to information, information that can be obtained from the firm's network. Partnering with firms with higher centrality provides benefits to the partner not only because of access to resources but because of the prestige associated with the higher centrality firm. Therefore, because the benefits associated with partnering with highly central firms outweigh the cost of willfully extracting knowledge, opportunistic behavior is reduced as firms with higher centrality can spread information about one's behavior in an alliance in its network. It may be difficult to form alliances with other firms in the network if one's reputation is damaged. Thus, when centrality is high in the alliance, firms act less opportunistically, and alliance-unrelated knowledge flows are reduced. Based on the above arguments, we hypothesize that:

Hypothesis 2: *The centrality of the partners in the network has a positive impact on the transfer of unintended knowledge flows.*

METHODS

Data and Sample

We used two main data sources to empirically evaluate our hypotheses: the Securities Data Company (SDC) Database on Joint Ventures and Alliances and the NBER patent database (Hall, Jaffe, and Tratjenberg 2001). SDC collects information about a variety of alliances from public sources such as SEC filings, industry and trade journals, and news reports. The sample consists of alliances formed between 1990 and 1996 involving shared R&D activities. In our approach to measuring knowledge flows, we use patent data to measure knowledge flows and therefore eliminated alliances that combine R&D activities with manufacturing and/or marketing activities and focused ourselves on alliances with a strong technological component. Due to two reasons, we only collected data up to 1996 inclusively. The first step in our knowledge flow assessment was to look at patent activity 10 years after the alliance. Second, the last year for which we have patent data from NBER is 2006. The period 1990-1996 also has the advantage of not containing any significant technological changes, thus avoiding any events such as patent races (Valentini, 2012). Studies that have looked at knowledge flows in previous literature use a comparable time frame to our study (e.g. Oxley and Wada (2009) use the period spanning 1988-1991 in their study; Sampson (2005) uses the period 1991-1993). Our sample is restricted to two partner alliances, where both partners are US private or public firms, thus maintaining consistency in patenting systems across nations. Our final sample is 613 alliances.

Additionally, we compiled a different data set with all the alliances from 1988-1996 to create the network measures. This resulted in 11,724 alliances. Some of the alliances have more than two partners, therefore we had a final number of 14,776 dyads. Since the termination date of the alliance is not reported, we assume that each alliance lasts three years, as in previous literature. Therefore, we created alliance networks based on a 3-year window, resulting in 8 snapshots for each industry (at the two digits sic level), for a total of 144 snapshots. In estimating the network measures, we used UCINET.

Measures

Several variables derived from patent data, mainly measures based on patent citations, are used as a proxy for knowledge flows between partners (Gomes-Casseres *et al.*, 2006; Mowery *et al.*, 1996; Oxley and Wada, 2009). Patents in the United States must cite all existing patents that are relevant to that technology, and thus patents provide evidence of an organization's knowledge-creation activities (Gittelman and Kogut, 2003; Vasudeva and Anand, 2011). Citations in patents are similar to citations in academic articles since both indicate previous work on which the current work is based (Gomes-Casseres *et al.*, 2006). Nevertheless, patent citations come with the advantage of being checked by an objective examiner. Examiners are experts "able to identify relevant prior art that the applicant misses or conceals." Therefore, examiners look at the accuracy of citations and make sure that the firm is not strategically disguising significant knowledge (Hall *et al.*, 2001) or that excessive citations to networks and colleagues are removed (Jaffe & Tratjenberg, 2002). Similar to Oxley and Wada (2009), in constructing our measures of related and unrelated knowledge flows, we used 118 technology classes defined in the International Patent Classification System which provide us with fine-grained measures of knowledge flows. The SDC database on alliances reports a scope for the alliance at the 4 digits SIC code. According to Schilling (2009), SIC coding in SDC is highly accurate. Thus, in identifying related and unrelated knowledge flows, we have to identify knowledge flows that are within the scope of the 4 digits SIC code of the alliance (related knowledge flows) and knowledge flows outside the scope of the alliance (unrelated knowledge flows). Unfortunately, the USPTO does not provide a SIC code for each patent. As a result, we use a concordance developed by Silverman, which has been used in previous literature (McGahan & Silverman, 2001), which connects the International Patent Classification (IPC) system to the U.S. Standard Industrial Classification (SIC) system at the four-digit SIC level.

This correspondence between patent classes and SIC provides the foundation for the distinction between related and unrelated knowledge transfers in alliances. First, we constructed patent portfolios for each of the firms in the alliance based on the SIC codes of the alliance. Patents belonging to these technological classes are considered alliance-related patents. The patents that belong to technological classes that are outside the scope of the alliance (outside the SIC code of the alliance) are considered alliance-unrelated patents. This method for calculating related and unrelated knowledge flows build on Oxley and Wada's (2009) study of alliance-related and unrelated knowledge transfers. Knowledge flows in related areas were measured as increases in citations to the licensor's patents by the licensee in those technological classes specifically covered by the licensed patents. Correspondingly, knowledge flows in unrelated areas were measured as the increase in citations to the licensor's patents by the licensee in technological classes outside those covered by the licensed patents. Based on these measures, Oxley and Wada (2009) argue that knowledge flows in alliance-related areas are intentional flows while knoalliance-unrelatedliance unrelated areas represent leakage rather than intentional knowledge sharing.

Variables

Prealliance Related Knowledge (Partner Pre-Citations in Alliance Related Areas)

For each firm, we must capture Prealliance Related Knowledge and Postalliance Related Knowledge. Since the application date is the earliest time when a new technology can be identified, we chose to look at the applied a date rather than the granted date (Rosenkopf and Almeida, 2003). The total number of patent citations to the partner in the alliance-related areas was counted in the patents applied for in the 10 years before the alliance. This count represents the Prealliance Related Knowledge.

Postalliance Related Knowledge

Similar to the prealliance-related knowledge, we counted the post alliance citations from firm *i* to firm *j* in patents applied for 10 years after the alliance in alliance related technological classes.

Related Knowledge Flows (R_i)

As $Firm_i$ acquires technological knowledge from its partner $Firm_j$ in an alliance we should see a higher rate of citation of $Firm_j$'s patents in new patents applied for by $Firm_i$ (Mowery *et al.*, 1996). Our final measure of related knowledge flows is the increase in cross-citations in the alliance related technological classes. This measure captures the extent to which one partner builds on the partner's technology in areas within the scope of the alliance.

Total Related Knowledge Flows ($\boldsymbol{TR_{ij}}$=$\boldsymbol{R_i + R_j}$) is the related knowledge flow in the alliance that is transferred from partner *i* to partner *j* summed with the related knowledge transferred from partner *j* to partner *i*. Thus, total related knowledge gives the sum of flow for both partners and is used to test the complementarity relationship between related and unrelated knowledge flows at the dyad level.

Prealliance Unrelated Knowledge (Partner Pre-Citations in Alliance Unrelated Areas)

The total number of patent citations was counted for the patents applied for in the 10 years before the alliance from firm *i* to firm *j* in the alliance unrelated technological classes.

Postalliance Unrelated Knowledge

Similar to the prealliance unrelated knowledge, we counted the postalliance citations from firm *i* to firm *j* in patents applied for 10 years after the alliance in the unrelated classes.

Unrelated Knowledge Flows (UR_i)

Increases in the cross citations in the unrelated technological classes constitute our final measure of unrelated knowledge flow for each firm. This measure captures the extent to which one firm builds on the technology of its partner, even though this is outside the scope of the alliance.

Total Unrelated Knowledge Flows ($\boldsymbol{TUR_{ij}=UR_i + UR_j}$) is the total unrelated knowledge flow in the alliance from partner *i* to partner *j* and from partner *j* to partner *i*.

Firm Centrality represents the position that a firm occupies within an alliance network. Centrality represents the number of nodes to which a focal node is adjacent. Degree centrality has been a measure widely used in the network literature (Powell *et al*., 1996). Because we have 144 different network snapshots, an important step was to normalize the degree centrality by the number of maximum possible degrees in an actor's network.

Control Variables

Total Number of Prealliance Patents. The total number of patents, a proxy for a firm technical capability, is an essential control variable based on patent data (Adegbesan & Higgins, 2011). We measure pre alliance patents by counting both partners' patents in the 10 years leading up to the alliance.

Total Number of Partner Pre-Citations in Related Areas was measured by counting both partners' Pre-Citations in Alliance Related Areas.

Total Number of Partner Pre-Citations in Unrelated Areas was measured by counting both partners' Pre-Citations in Alliance Unrelated Areas.

Technological Overlap. Following prior research, we use the measure of technological overlap developed by Jaffe (1986) based on the angular separation of the patent class distribution vectors of the partner firms in the 10 years before the announcement of the alliance. Technological Overlap varies from zero to one. A value of zero indicates no overlap in partner firms' areas of technological expertise and the closer the value is to one, the greater the overlap.

Industry Dummies. Firms in different industries have different patenting propensity due to differences in the importance of patent protection, technological advancement etc. (Mansfield, 1986).

Year Dummies. Since the propensity to patent may also vary across time (Pavitt, 1984), we control for the year when the alliance was announced.

Joint Venture. Since previous literature has made the point that knowledge is enhanced in Joint Ventures and related knowledge flows is enhanced in JVs while unrelated knowledge flows are reduced in JVs (Mowery *et al*., 1996; Oxley and Wada, 2009) we introduce a dummy variable control for whether the alliance is organized as a Joint Venture (equals 1), or it is a contract-based alliance (equals 0).

Alliance Experience. To capture a firm's prior alliance experience (Hoang and Rothaermel, 2005) we counted from SDC the total number of formed alliances before the alliance.

Network Average Density is defined as the extent to which the actors in a firm's network are connected. This measure was calculated, using UCINET, as the total number of ties divided by the total number of possible ties.

Statistical Methods

We use a negative binomial model as our methodology. We have a high number of zero values in our dependent variables since we use patents to measure alliance-related knowledge flows and alliance-unrelated knowledge flows. A negative binomial model accounts for the dependent variable's count nature as well as its overdispersion (Sampson, 2007; Stuart, 2000). To test hypotheses 1 and 2 we ran two separate regression models at the dyad level with total related flows and total unrelated flows as the dependent variables.

Further, we ran a robustness check at the individual firms' level in the alliance rather than at the dyad level. Kenny, Kashy, and Cook (2006) recommend that when the dyadic analysis is done, firms in the dyad should be assigned to each group based on a meaningful variable. Since we are interested in how centrality impacts alliance-related and alliance-unrelated knowledge flows, we decided to divide the sample of dyads (*i*,*j*) into two vectors such that *Centrality i*> *Centrality j*. The vector *i* thus comprises firms drawn from each dyad that have relatively higher Centrality than their partners. The vector *j* correspondingly contains partner firms that have relatively lower Centrality than their partner. Multiple alliances were formed by some firms during our sample period. Thus, the disturbances for these firms are not independent. To correct for this lack of independence between observations, we clustered the errors on the focal firm.

RESULTS

Table 1 presents the descriptive statistics for the dyadic analysis. All correlations in table 1 are within the adequate range specifying slight concerns related to multicollinearity.

TABLE 1
CORRELATION TABLE AND DESCRIPTIVE STATISTICS

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total related knowledge	1									
Total unrelated knowledge	0.74	1								
Degree Centrality	0.16	0.12	1							
Network Density	-0.01	-0.06	0.49	1						
Total Number of Partner Pre-Citations in Related Areas	0.59	0.52	0.17	0.08	1					
Total Number of Partner Pre-Citations in Unrelated Areas	0.43	0.56	0.16	0.06	0.73	1				
Total Number of Prealliance Patents	0.31	0.29	0.28	0.001	0.45	0.43	1			
Joint Venture	-0.01	-0.03	0.06	0.15	0.04	0.02	0.0002	1		
Technological Overlap	0.40	0.35	0.09	-0.1	0.37	0.27	0.17	0.024	1	
Alliance Experience	0.39	0.31	0.35	-0.05	0.42	0.38	0.71	0.017	0.269	1
Mean	01.21	4.99	.028	.01	9.43	1.58	1558.9	.0633	.234	95.28
Standard Deviation	64.91	8.43	.051	.01	33.54	6.40	2198.3	.243	.311	140.17

In Table 2, column 1 presents the results for the regression at the dyadic level when the dependent variable is Total Related Knowledge Flows. The coefficient estimate for *Partners' Centrality* is positive and significant indicating overall support for our hypothesis 1 that alliance-related knowledge flows are enhanced by the partners' centrality. Thus, network centrality enhances collaboration leading to more knowledge flows within the scope of the alliance.

In Table 2, column 2 presents the results for the regression when the dependent variable is Total Unrelated Knowledge Flows. The coefficient estimate for *Partners' Centrality* is negative and significant indicating support for Hypothesis 2 that alliance-unrelated knowledge flows are diminished by the partners' centrality. Partners' centrality acts as a predictor for opportunistic behavior and thus the higher the centrality of the partners, the lower the transfer of knowledge in areas outside the scope of the alliance.

TABLE 2
IMPACT OF PARTNERS' CENTRALITY ON RELATED AND UNRELATED KNOWLEDGE – DYAD LEVEL NEGATIVE BINOMIAL ESTIMATES

VARIABLES	(1) Total Related Knowledge Flow	(2) Total Unrelated Knowledge Flow
Partners' Centrality	24.452**	-7.305*
	(7.930)	(3.560)
Network Average Density	-105.049***	46.697
	(24.403)	(30.854)
Total Number of Partner Pre-Citations in Related Areas	0.018	0.011*
	(0.011)	(0.006)
Total Number of Partner Pre-Citations in Unrelated Areas	0.001	0.053*
	(0.040)	(0.023)
Total Number of Prealliance Patents	0.000***	0.000***
	(0.000)	(0.000)
Year Dummies	Included***	Included***
Industry Dummies	Included***	Included***
Joint Venture	-0.706	0.518
	(0.446)	(0.425)
Technological Overlap	5.269***	5.234***
	(0.660)	(0.562)
Alliance Experience	-0.001	0.004*
	(0.002)	(0.001)
Constant	-0.103	-1.648**
	(0.679)	(0.608)
Wald Chi	1791.10***	367.73***
Df	21	21
Observations	597	613

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

In Table 3, we present our robustness checks. Column 1 presents the results for the regression at the individual firm level when the dependent variable is Related to Knowledge Flows for the firm in the dyad that has relatively lower centrality than its partner. The coefficient estimates for *Partner' Centrality* is positive and significant indicating support for the idea that related knowledge flows is enhanced by the partner's centrality which has more access to knowledge in the network.

In Table 3, column 2 presents the results for the regression when the dependent variable is Firm Unrelated to Knowledge Flows. The coefficient estimate for *Partners' Centrality* is negative and significant indicating support for Hypothesis 2 that unrelated knowledge flows are diminished by the partner' centrality. Because central firms have more access to resources it becomes more desirable to ally with a central firm. Being deeply embedded in the network, firms have a high number of connections with other influential firms and have access to their resources (Lavie, 2007). Most of the time, higher centrality means more access to resources. Higher centrality implies that opportunism will decrease, as this firm can sanction opportunistic behavior more efficiently. Further, when partnering with a firm with high centrality, the benefit from opportunistic behavior will not outweigh the benefits that could result from the success of this alliance (e.g., accessing the partner's network resources), the partner will limit its opportunistic behavior, and therefore its inflows of knowledge in alliance unrelated areas.

TABLE 3
IMPACT OF PARTNER'S CENTRALITY ON RELATED AND UNRELATED KNOWLEDGE – INDIVIDUAL FIRM-LEVEL ANALYSIS
NEGATIVE BINOMIAL ESTIMATES

VARIABLES	(1) Firm Related Knowledge Flow	(2) Firm Unrelated Knowledge Flow
Partner Centrality	44.239***	-16.416*
	(12.066)	(8.969)
Firm Centrality	71.430**	60.513**
	(27.285)	(20.812)
Network Average Density	-156.272***	-20.208+
	(25.114)	(12.097)
Total Number of Partner Pre-Citations in Related Areas	0.002	0.011**
	(0.007)	(0.003)
Total Number of Partner Pre-Citations in UnRelated Areas	0.038	0.002
	(0.033)	(0.015)
Firm Prealliance Patents	0.000**	0.000+
	(0.000)	(0.000)
Partner Prealliance Patents	0.000*	0.000***
	(0.000)	(0.000)
Year Dummies	Included***	Included***
Industry Dummies	Included***	Included***
Joint Venture	-0.221	1.406*
	(0.510)	(0.700)
Technological Overlap	3.899***	2.962***
	(0.530)	(0.523)
Total Alliance Experience	-0.001	0.001
	(0.002)	(0.002)
Partner Related Knowledge Flow	0.003***	
	(0.001)	
Partner Unrelated Knowledge Flow		0.030***
		(0.006)
Constant	-2.579***	-2.951***
	(0.558)	(0.663)
Wald Chi	797.29***	370.46***
Df	22	22
Observations	457	468

Robust standard errors in parentheses with clustering on the focal firm. Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

DISCUSSION

Researchers have long been interested in alliances as a mechanism for acquiring knowledge. Acquiring knowledge is important for firms as it leads to increased ability of creating new products (Rosenkopf and Almeida, 2003) and it is even more important in high paced industries (Powell, Koput, & SmithDoerr, 1996). Nevertheless, there have been limited studies focused on understanding the different types of knowledge flows within an alliance and the factors that hinder or contribute to these types of knowledge flows. In this study, building on the work of Oxley and Wada (2009) we break down knowledge transfers in alliances into two categories: knowledge flows that are within the scope of the alliance and knowledge flows that are outside the scope of the alliance. Additionally, we have examined whether these types of knowledge flows (inside and outside the scope of an alliance) are impacted by the network centrality of the partners. Knowledge flows within the scope of the alliance are intentional while knowledge flows outside the scope of the alliance occur mainly due to leakage and appropriability hazards (Oxley and Wada 2009). Previous literature has suggested several mechanisms to promote knowledge flows within the scope of the alliance or to reduce the knowledge flows outside the scope of the alliance such as limiting the scope of the alliance and using equity to align partners' incentives. Interfirm network structure and thus centrality is a predictor for cooperative, but also opportunistic behavior. The combined centrality of the partners positively impacts the knowledge in alliance-related areas that both partners receive while negatively impacting the alliance-unrelated knowledge flows. Amesse and Cohendent (2001) argue that the operation of alliances depends largely on trust. Partnering with a firm with high centrality can be an important basis for enforcing trust. When partners in an alliance have high centrality, these higher centrality firms have likely developed behavior that fosters cooperation and trust. The behavior of one partner is likely to be reported to other actors in the network. Most likely reputation will be affected, and future collaboration might be compromised if opportunistic behavior is exhibited. Therefore, the higher the centrality of one firm, the higher the chances that its partner's behavior will be reported in the firm's network.

Partners are different in how they act to accomplish their goals and may behave opportunistically. When allying, firms should expect their partner to act opportunistically and therefore should choose their partners carefully. It is always ideal to partner with a firm that has higher centrality and thus higher access to knowledge. However, firms partnering with high-centrality firms should be careful in acting opportunistically and willfully extracting knowledge that is outside the scope of the alliance as firms with higher centrality can sanction this behavior. We showed here that the knowledge the firm with lower centrality receives and falls within the scope of the alliance is possibly impacted by the centrality of the firm with higher centrality in the dyad. Further, the transfer of knowledge in alliance-unrelated areas to the firm with lower centrality is limited by the centrality of its partner with higher centrality. Thus, when establishing the goals of an alliance, close attention should be paid to the centrality of the partner since their centrality could be a means for limiting opportunism and enhancing cooperation.

This study has limitations inherent in patent data. One of the limitations of patent data is that the commercial importance of patents as also as the propensity to patent in each industry is different. We included industry controls in the regressions to account for this limitation. Despite the existing limitations in patent data, patent citations continue to be an accepted measure of the knowledge flow between partners. We hope future studies explore primary sources of data collection for measuring knowledge flows.

Future research could build on this paper in various ways. First, it would be useful to re-examine our findings in alternative samples and settings. Also, it is possible that rules that reduce the risk of unintended knowledge transfer can at the same time reduce intended knowledge transfer. Other factors could impact in the same direction both alliance-related and alliance-unrelated knowledge. Organizations can risk low intended and unintended knowledge transfer by taking too many protective measures or can risk depreciation of knowledge assets by transferring too much. A balance between these two must be found to achieve alliance success.

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