COORDINATING COMPLEX WORK:

KNOWLEDGE NETWORKS, PARTNER DEPARTURES

AND CLIENT RELATIONSHIP PERFORMANCE IN A LAW FIRM[*]

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ABSTRACT

The mobility of individual managers has long presented a problem for firms in knowledge-intensive industries. Shifting to more complex work often reduces the importance of a single individual's knowledge for the firm's exchange relationships because complex work requires inputs from a broader set of the firm's members. Although complex work decreases the likelihood that a single individual can shift the exchange relationship to another firm, we propose that it increases the vulnerability of the firm's performance to departures of those individual managers who act as coordinators of knowledge. This leads us to focus on how the internal knowledge network formed to maintain each relationship can compound or mitigate the loss of a coordinating manager. Using original data on client relationships from a law firm, we examine the effect of internal knowledge networks and lead partner departures on the performance of the relationships. Supporting our argument, we find that the negative performance effect of a lead partner departure is greater when the network has high knowledge heterogeneity and involves more experts and lower when the network has high cohesion.

The mobility of individual managers has long presented a problem for firms in knowledge intensive industries. Managers create and apply knowledge to the firm's exchange relationships, and so, perhaps not surprisingly, scholars have shown a close correlation between the stability of individual relationships and interorganizational exchange (Baker, Faulkner and Fisher 1998, Broschak 2004, Dokko and Rosenkopf 2010). This problem is most evident when a single individual provides the knowledge needed by the exchange partner, making it easier for a departing manager to transfer the exchange relationship to another firm. However, the circumstances under which that departure may be more or less harmful are less well understood.

In this study, we propose that the performance consequences of manager departures for firms depend in part on the complexity of work overseen by the manager. For firms, shifting to more complex work is one means of reducing the importance of a single individual's knowledge for the firm's exchange relationships. In complex work, a number of different items or elements must be dealt with simultaneously by the organization (Scott 1992: 230), and inputs from multiple members across the organization are needed (Cross, Ehrlich, Dawson and Helferich 2008, Cummings and Haas 2012, Tushman 1979). Furthermore, the need for expert knowledge to complete complex work necessitates broader search within the firm. Thus, complex work regularly leads to the formation of more heterogeneous, dispersed knowledge networks. Not only do these types of networks have the potential to reduce the ease with which a single individual can shift the exchange relationship to another firm, but they also may facilitate learning and creativity, resulting in a higher level of overall performance for the firm (Reagans and Zuckerman 2001).

Yet complex work also requires greater coordination (Cummings and Cross 2003, Perrow 1967). Coordination involves "integrating or linking together different parts of an organization to accomplish a collective set of tasks" (Van de Ven, Delbecq and Koenig 1976: 322). Knowledge required to do complex work may come from members of the firm who are distant from one another, both in terms of geographic location and knowledge domain. When the knowledge network formed is not sufficiently coordinated, the returns to the firm are lower (Boh, Ren, Kiesler and Bussjaeger 2007). Furthermore, as work becomes more complex, formal programmed means of coordination are not applicable (Van de Ven et al 1976, Thompson 1967), and alternative means of coordination are needed. In particular, greater complexity increases the need for a central coordinating actor, i.e. a broker, in the knowledge network (Lawrence and Lorsch 1967, Lingo and O'Mahony 2010, Obstfeld 2005). Considered this way, complex work may actually increase the vulnerability of the firm to departures of individual managers when they serve as coordinators of knowledge.

To investigate the variation in the performance consequences of manager departures, we examine the effects of client lead partner departures from a law firm on the subsequent performance of their client relationships. In this setting, serving clients requires coordinating the knowledge of members of the firm. As the complexity of client needs increases, this involves greater coordination across different intraorganizational domains of expertise and geographic jurisdictions. The knowledge networks assembled to serve such clients span geographies and knowledge areas and often involve multiple high status knowledge experts from the firm. In such cases, programmed coordination is likely to be less effective because of the complexity of the work, and the role of the client lead partner as a coordinator of the network should become increasingly important. Hence, the performance decline following the departure of the lead partner should be greater for client relationships involving such complex work.

Using fine-grained data on the full set of partners and clients of a large US-based corporate law firm, we examine the impact of a client lead partner departure on the billable hours for that client account. Billable hours is a key measure of the performance of each client relationship for the law firm. To serve clients, client lead partners assemble internal networks to access the relevant expertise of the firm's lawyers, and these networks reflect the underlying complexity of the clients' needs. In large law firms like the one we study, complex work is typically associated with internal networks that span different offices and practice areas, and which include "star" lawyers and involve lawyers who are not interacting on other client accounts (Gardner 2014a, 2014b). Thus, although we could not directly observe the complexity of work, with our fine-grained data we can accurately observe the networks formed to serve each client. Our main argument is that the negative performance impact of the client lead partner departure will be higher for client relationships with internal networks associated with complex work because the client lead partner plays a greater coordination role in these networks.

Consistent with prior work, we find that lead partner departures have a negative main effect on performance. Supporting our arguments, our analyses show that post-departure performance declines further as the level of knowledge heterogeneity in the network rises, as well as when the knowledge network includes multiple high status knowledge experts. In contrast, however, we also found that when the cohesion of the knowledge network is high (i.e., when the network includes lawyers who are interacting on other accounts), the post-departure performance drop is attenuated. Furthermore, we find that cohesion reduces the negative effect of lead partner departures when networks have high knowledge heterogeneity. The pattern of findings suggests that performance losses associated with managerial mobility are in part a function of the coordination roles played by departing managers, and that this coordination becomes increasingly important for complex work.

This study extends research on managerial mobility (Bermiss and Murmann 2014, Broschak 2004, Carnahan et al. 2012, Dokko and Rosenkopf 2010, Somaya et al. 2008) by providing arguments and support for the moderating role of the internal knowledge networks maintained by managers on the relationship between the departure of these managers and relationship performance. Our findings also inform research into the fundamental trade-offs firms face in organization design (e.g., Eisenhardt, Furr and Bingham 2010, Krestchmer and Puranam 2008, Lawrence and Lorsch 1967). We find that although heterogeneous knowledge networks are associated with high performance before a law firm partner's departure, they are associated with the lowest performance post-departure. Thus, professional service firms face a dilemma between encouraging the development of knowledge networks that deliver the greatest value when partner mobility is low, and protecting the firm from performance declines associated with such networks when mobility is high. Lastly, our findings also have important implications for research on complexity and network dynamics (e.g., Amaral and Uzzi 2007, Csermely, London, Wu and Uzzi 2013). As we argue and show here, as work becomes more complex, the need for additional coordination mechanisms increases, and the vulnerability of firms to departures of coordinating brokers increases.

PERFORMANCE EFFECTS OF MANAGER MOBILITY

Over the past few decades, evidence of increasing levels of managerial and professional mobility has accumulated (e.g., Bidwell, Briscoe, Fernandez-Mateo and Sterling 2013, Cappelli 1999). Average organizational tenure for managers has declined as individuals increasingly move between firms. These individual moves are often accompanied by moves of clients or other exchange partners. Indeed, the observed link between individual mobility and the instability of exchange suggests that the evolution of inter-organizational networks is shaped in large part by the dynamics of the individual-level networks among firms (e.g., Broschak 2004, Rogan 2014a).

Accordingly, the mobility of managers and related performance consequences for firms has been the subject of considerable research. The majority of studies provide evidence of negative performance effects for the firm losing the manager. Arguments for these performance effects generally rely on one of two main causal mechanisms. The first is the loss of human capital, including the transfer of knowledge and routines to other firms that accompanies the loss of managers. Consistent with this explanation, Aime, Johnson, Ridge and Hill (2010) found that a firm's loss of managers to competitors decreased the firm's performance relative to its competitors due to the transfer of knowledge and routines to the competitor. Similarly, Campbell, Ganco, Franco and Agarwal (2011) provide evidence of a negative performance effect following departures of managers who start their own companies imitating their prior firm's routines. The performance consequences can be considerable. Both Phillips' (2002) study of law firms and Wezel, Cattani and Pennings' (2006) study of accounting firms showed that losing employees to other firms, especially competitors, significantly decreased a firm's survival likelihood.

The second mechanism cited in the literature is the loss of external social capital by the firm when its managers move. As argued by Dokko and Rosenkopf (2010) mobile individuals carry social capital, which has performance consequences for the firms they leave and the firms they join. In research on the mobility of managers in the advertising industry, the loss of managers is positively related to the loss of clients (Broschak 2004), and clients regularly follow managers to their new advertising agencies (Broschak and Niehans 2006). Similar to the evidence regarding the human capital effects of manager mobility, Somaya, Williamson and Lorinkova (2008) found that it was more harmful for a firm to lose managers and their social capital to competitors than to other organizations. Lastly, in contrast to the predominate view that losses of managers have negative performance consequences for firms, Corredoira and Rosenkopf (2010) and Godart, Shipilov and Claes (2014) find that the prior employer can actually benefit. The transfer of managers to and from firms generates communication channels between both firms, which can be considered part of the social capital of both firms. In this way, the social capital of departing employees facilitates reverse knowledge and talent flows back to the prior employer.

In summary, although under some conditions firms benefit from outflows of managers, in general, the loss of managers has been associated with a decrease in performance either due to a loss of human capital or external social capital. To be sure, existing approaches to the question of the performance effects of manager departures have greatly expanded our understanding of when departures are more problematic to firms. However, the variance in the performance consequences of manager departures remains less well understood. Below we introduce a third mechanism involving the internal knowledge network of the departing manager and the role it plays in the performance effect of the manager's departure from the firm. In particular, we expect that the extent to which the manager must coordinate the knowledge network will have implications for the impact of the manager's departure. As work becomes more complex, the role of the manager as a coordinating broker in the knowledge network becomes more important, and thus, the manager's departure becomes more – not less – consequential for the performance of the firm's exchange relationships.

KNOWLEDGE NETWORKS

The idea that characteristics of networks aid knowledge sharing, which has a positive effect on performance, is well established in the literature (Nerkar and Paruchuri 2005, see Phelps, Heidl and Wadwa 2012 for a review). Certain network characteristics have been found to improve access to knowledge as well as the ability to use knowledge. For example, strong ties in a network are associated with the ability to obtain tacit knowledge from others and to apply this knowledge effectively (Hansen 2002). Likewise, the diversity of a network improves the positive relationship between knowledge sharing and group performance (Cummings 2004) and increases productivity (Reagans and Zuckerman 2001).

Nevertheless, the transfer of knowledge inside firms is often difficult (Haas 2006a, 2006b, Szulanski 1996) and mechanisms to coordinate knowledge are needed to realize performance benefits (Thompson 1967). In foundational research on the coordination of work, March and Simon (1958) proposed that coordination could be either programmed or based on feedback and mutual adjustments. As further noted by Thompson (1967), coordination by feedback occurs both via a personal mode, in which an individual serves as the mechanism for making mutual task adjustments, and via a group mode, in which a group of members serves as the mechanism for adjustments. Building on these ideas, Van den Ven and colleagues (1976) classified coordination into three alternative modes – impersonal, personal and group – and offered arguments and evidence for when certain types of coordination modes would be more or less effective. In particular, they found that as tasks become uncertain and variable, impersonal coordination decreases while personal and group coordination increase.

Complex work, which is characterized by task uncertainty and variability, entails a shift from impersonal coordination mechanisms to coordination by a central actor or coordination by the group.[1] Prior theory suggests that as work becomes more complex, the knowledge networks formed to complete it become more heterogeneous and draw on more expert knowledge (Cross et al. 2008, Cummings and Haas 2012). Both of these increase the need for coordination of knowledge in the network. First, as members of the knowledge network are more heterogeneous, i.e. dispersed across geographies or knowledge domains, it becomes increasingly difficult and costly to coordinate the knowledge of network members (Foss et al. 2010, Mors 2010, Mortensen 2015). Second, although experts bring valuable knowledge needed for

[1]On its own, mere variability in work inputs or demands can be accurate modelled, resulting in coordination through work routines. But when work is also uncertain, implying a lack of clarity regarding the performance or effects of work efforts (Van de Ven, et al., 1976), work cannot be pre-programmed into routines. It is under these conditions that informal coordination by a person or a group becomes important.

complex work, when a network includes multiple experts, members may be uncertain about which expert's routines should take precedent. Accordingly, programmed means of coordination, which work best for simple, predictable work, are less effective. Furthermore, because complex work often involves more members from distant parts of the organization in the network, the average cohesion of the network is likely to be lower (Van de Ven et al. 1976). With lower cohesion among members, i.e. fewer prior connections via previous projects, informal coordination via the group mode is limited and the need for an alternative coordination mechanism increases. As noted by Van de Ven and colleagues (1976), in this case the need for coordination by a central actor (i.e. personal mode) increases.

In law firms, the context for this study, knowledge networks are regularly formed inside firms to apply knowledge in developing solutions for a client's needs. Typically, one partner serves as a client lead partner, interpreting and anticipating the client's needs and forming connections inside the firm with lawyers holding relevant knowledge. Lawyers have a high level of autonomy over their work and choose whether or not to contribute to the client relationship. They work on legal matters (i.e. projects) for more than one client, and therefore, their knowledge may be required for several clients at a given time. Client lead partners play an important role coordinating this knowledge as described by Teece (2003: 903): "Partners (senior talent) frequently need to access other senior talent in order to meet client needs. Partners also need to harness the resources of other partners to bring work in the door." However, the importance of this role varies with the complexity of the work. For non-complex work, existing routines and procedures can guide the work. In contrast, when the work is complex, an additional coordination mechanism is required, and the firm's dependence on the client lead partner as a coordinating broker is likely to increase.

Knowledge heterogeneity

A key feature of knowledge networks is the extent of knowledge heterogeneity within them. In complex work, knowledge heterogeneity improves performance by bringing non-redundant and varied information to the group, which can then be recombined to develop novel solutions, and in turn improve performance (Reagans and Zuckerman 2001, Rodan and Galunic 2004). Knowledge heterogeneity describes the extent to which the internal network includes ties to others providing unique knowledge and information. When knowledge is sourced from a more distant contact--i.e., someone who is geographically removed or from a different area of expertise—it tends to be less redundant. For example, research has shown that knowledge transferred across geographically distant contacts is more novel and less homogenous than knowledge transferred across geographically proximate contacts (Bell and Zaheer 2007). Similarly, in a study of knowledge sharing among groups in a Fortune 500 firm, Cummings (2004) found that the more the group spanned geographic locations, functional assignments, reporting managers or business units, the positive relationship between knowledge sharing and group performance increased.

In legal services, the combination of knowledge from different expertise domains and across different geographical jurisdictions often leads to better solutions for clients with complex needs. For example, Briscoe and Tsai (2011) described a litigation partner whose frequent collaborations with colleagues from the corporate transactions department led him to develop novel solutions to anti-trust issues, normally the domain of corporate, that incorporated related litigation issues. Likewise, a partner whose client is facing a difficult lawsuit in one state jurisdiction may offer better advice by integrating the opinions of colleagues who know the relevant cases and members of the judiciary ruling on them in other court jurisdictions. Further, over time, as clients see the knowledge network in use in these productive ways, they may give more work to the firm because they gain confidence in the depth and breadth of expertise available to them at the law firm. Holding all else equal, the more that the lead partner draws upon diverse knowledge in the firm to serve the client, the higher the performance of that client relationship is for the firm.

Yet, heterogeneity can harm performance if it exceeds the capacity for knowledge integration (Pfeffer 1983). Higher levels of heterogeneity require greater coordination to realize performance benefits (Rulke and Galaskiewicz 2000). For example, in a study of a non-profit research organization, Boh and colleagues (2007) show that geographic dispersion among members when executing more complex work generates higher net earnings, but too much dispersion increases coordination costs and leads to lower earnings. To the extent that the partner is playing a coordinating role, the removal of the lead partner decreases the capacity for coordination. When heterogeneity is low, coordination needs are low, so the partner's departure should not change the effect of heterogeneity on client relationship performance. However, when knowledge heterogeneity is high, the need for coordination is high. In this case, the level that was manageable when the lead partner who assembled the knowledge network was in place exceeds the capacity that exists when the partner leaves. Moreover, because the coordination often occurs via informal means (Hansen 2002, Tsai 2002), following the departure of the partner, on average, the new client lead partner will be less able to effectively coordinate the knowledge of the network assembled by the departing lead partner. Thus, in complex work, when the need for coordination due to greater heterogeneity is high, the drop in the performance of the client relationship for the firm should be greater when the client lead partner leaves.

Heterogeneity in knowledge networks in a law firm can exist in either the domains of expertise that are applied to the client relationship or the geographic reach of the network. For example, the knowledge network for a pharmaceutical client may include partners specializing in intellectual property, health care, general litigation, and corporate acquisition transactions. That knowledge network may also span the law firm’s offices in multiple U. S. states, in part reflecting the different state jurisdictions where the client has operations. Our arguments above suggest that realizing the ongoing benefits of either type of knowledge heterogeneity - domain heterogeneity or geographic heterogeneity - is contingent upon the coordination capacity of the lead partner. Thus,

Hypothesis 1. The negative effect of the departure of the client lead partner from the firm on the client relationship's performance will increase with the (a) domain heterogeneity and (b) geographic heterogeneity of the knowledge network.

Multiple experts

In addition to drawing upon knowledge from heterogeneous areas, complex work often requires bringing in experts. Experts are considered among the best in their fields and consequently are afforded power and status within the firm and industry (French and Raven 1959). As described by Teece (2003: 896), "Experts are those privileged individuals who through superior education, experience, position (e.g.

former public officials) or performance somehow get recognized by society as leaders in their field. Once so anointed, the experts can almost 'write their own ticket,' and will wish to have their work preferences recognized…." As noted by Bunderson and Barton (2011), when work is complex, it is no longer clear what specific knowledge and expertise is needed to complete the work. Group members instead default to diffuse expert status cues such as awards, external rankings or relative standing within the firm rather than specific cues; and hence such recognized experts are often involved in complex work.

The performance of a group can benefit from having more expert members for several reasons. First, the high status afforded to experts means they have superior access to resources and influence and can bring these to bear on the tasks at hand (e.g. Boynton and Fischer 2005, West 1994). Second, as demonstrated in prior research, experts also have a higher willingness than non-experts to share their knowledge with others (Thomas-Hunt, Ogden and Neale 2003). Third, as a function of their prior success, experts have deep knowledge about how to define problems, which is particularly valuable when the complexity of problems is high. They have developed meta-routines and mental representations for their work, which can be applied to the task at hand (Glaser 1999). Thus, to the extent that group performance is a function of the performance of individuals comprising the group, having experts as members yields performance benefits.

Despite these benefits, having multiple experts also can increase coordination difficulties. Expert knowledge is embodied in individual experience and comprises wisdom of technique (Morris and Empson 1998). Experts hold deeply entrenched cognitive structures and practice routines that have developed and crystallized over the course of their prior successes. When experts confront new problems, they quickly generate mental representations of the problem linked to their own knowledge base, and they draw inferences and formulate plans based on analogies between the current problem and those they encountered in the past (Marchant and Robinson 1999, Patel, Arocha and Kaufman 1999). Hence when a knowledge network includes more than one expert, other group members may become confused about whose routines and representations to adopt. In addition to causing direct conflict between experts (e.g., Groysberg, Polzer and Elfenbein 2011, Swaab et al. 2014), this confusion leads to coordination difficulties because other group members remain uncertain about whose routines to follow in their work (Joshi and Knight 2015). For example, illustrating the problems caused by conflicting routines, Gardner and Valentine (2014) relate a law firm partner's description of the difficulties of working with one of his firm's experts in employment law: "…We have to adapt to their expectations about response times, terminology, even formatting. It might sound trivial, but when you try to deliver a joined-up approach, there are real tussles about who's right." (Gardner and Valentine 2014: 42). To be sure, part of the value of experts is their ability to conceive of mental representations for structuring – and ultimately solving – these complex problems. Yet, the superiority of one routine or representation over another is a subjective matter, and thus when complex work requires more than one expert to be in the network, uncertainty arises as to which representation to adopt.

The uncertainty surrounding which routine or mental representation to adopt increases the need for coordination, and this need is even greater when formal hierarchical structure is limited (Ronay, Greenaway, Anicich and Galinsky 2012). One means of resolving the confusion is for a central actor to coordinate the routines and representations of the experts needed for complex work. This coordination can occur via integration or differentiation (Dougherty 2001, Lawrence and Lorsch 1967). In integration, a central actor facilitates joint problem solving by multiple experts, and routines are blended or modified when applied to the work. In differentiation, they are applied independently to select areas of the work as directed by a central actor. Regardless, confusion among expert routines is likely to reduce the performance gains associated with tapping into expert knowledge without sufficient coordination.

In law firms, although the identification of experts is not usually problematic, the knowledge networks have limited formal hierarchical structures and so formal coordination is limited. Expert lawyers represent the top talent of the firm and have resources under their control that can be brought to bear on the client relationship. Thus, client lead partners have a motivation to draw upon the knowledge of expert lawyers when the needs of clients are complex. Nevertheless, having multiple experts can create confusion about which routines to adopt. The client lead partner must coordinate the individual expert contributors to the knowledge network to realize the benefits of their knowledge, ensuring that frameworks, assumptions, and client interactions are harmonized across individuals who work with the client. Therefore, the departure of a client lead partner will be especially problematic for the performance of the client relationship when the work requires the involvement of multiple experts, due to the potential conflict over routines and representations in the knowledge network. Formally,

Hypothesis 2. The negative effect of the departure of the client lead partner from the firm on the client relationship's performance will increase with the extent to which the knowledge network includes expert knowledge.

Cohesion

While knowledge heterogeneity and multiple experts in the knowledge network give rise to a need for personal coordination, greater cohesion among members of the knowledge network offers an alternative means of coordination that should lower the need for coordination by a lead partner. As noted above, in complex work, coordination by mutual adjustment occurs via a personal mode and a group mode (Thompson 1967, Van de Ven et al. 1976). Whereas the personal mode of coordination is represented by the presence of a central actor, the potential for group mode of coordination depends in part on the extent to which knowledge network members are linked directly with one another rather than only via the central actor, or in other words by the cohesiveness of the knowledge network.

Cohesion in a knowledge network arises from the density of connections existing among the members of the network. It is associated with trust, enhanced information sharing, and enforceability of norms (Coleman, 1988). Trust generated by cohesion increases the motivation of network members to invest time and effort in knowledge sharing (Reagans and McEvily 2003). The ability of members to share knowledge is also enhanced because members of cohesive networks share a common language and understanding and are more aware of the knowledge held by other members of the network (Nahapiet and Ghoshal 1998, Wegner 1987). For example, prior research on student groups has shown that members with prior ties to one another are better able to recognize other members' expertise, which facilitates group performance (Lewis 2004). Furthermore, members of cohesive networks are less likely to violate group norms by refusing to share knowledge with other members.

Empirical evidence supports arguments concerning the benefits of cohesion for knowledge sharing and subsequent performance. Studies of knowledge transfer in R&D divisions demonstrate a positive effect of network cohesion on knowledge transfer across units (e.g. Reagans and McEvily 2003, Tortoriello, Reagans and McEvily 2012). Local cohesion among a firm's R&D scientists is positively associated with the innovative performance of firms (Guler and Nerkar 2012). Similarly, Rulke and Galaskiewicz (2000) found that the performance of groups of specialists was greatest when members were directly connected to one another via strong ties. A meta-analysis of 37 studies of teams by Balkundi and Harrison (2006) showed that teams with densely configured internal ties, i.e. higher cohesion, attained their goals better than other teams.

In the law firm we study, cohesion among lawyers from the same knowledge network increases when those lawyers work together on projects for other clients, for example preparing arguments together to be used in court for a client. The additional ties among other members of the network provides opportunities for the formation of trust, enhanced knowledge sharing and enforcement of norms in the knowledge network, which in turn aids coordination independent of the client lead partner. Thus, in contrast to our predictions for knowledge heterogeneity and expert knowledge, we expect that greater cohesion in the knowledge network will reduce the negative effect of lead partner exit on performance. Formally,

Hypothesis 3. The negative effect of the departure of the client lead partner from the firm on the client relationship's performance will decrease with greater cohesion in the knowledge network.

When work is complex, and the network has greater knowledge heterogeneity and multiple experts, the average cohesion of the network is likely to be lower. This is because complexity increases the need to search for novel solutions, which depends on having sparse, broad knowledge networks. Therefore, for most knowledge networks, we expect that the coordination provided by the client lead partner will be critical, and that the departure of the client lead partner will lead to lower performance when the networks have high knowledge heterogeneity and multiple experts. However, in those uncommon circumstances when the network also has high cohesion, the dependence on the client lead partner as a coordinating broker should be lower and the negative performance consequences of losing the client lead partner should be lower. With high cohesion coordination by the group offsets the coordination losses associated with the departure of the client lead partner. Thus in addition to negatively moderating the effect of the departure of the client lead partner on performance, cohesion should further reduce the additional negative effect of the lead partner departure from complex work networks. Formally,

Hypothesis 4. The negative interaction effect of the departure of the client lead partner from the firm and (a) high domain heterogeneity, (b) high geographic heterogeneity or (c) expert knowledge on the client relationship's performance will decrease with greater cohesion in the knowledge network.

METHODS

Setting and data

Our data come from the internal records of one large corporate law firm during the years 1998 to 2007. In most important respects, this firm was typical of other firms in the American corporate legal services industry operating during the 1990s and 2000s. These firms are classic professional service firms that are high in knowledge intensity and low in physical assets, and their principal activities involve providing professional advice and services to clients (Greenwood, Suddaby and McDougald, 2006, von Nordenflycht 2010). The firm provided a range of legal services to corporate clients in many industries, and held offices in several US cities. Among corporate law firms, this firm was relatively large, employing more than 2,000 individuals. The great majority of the firm's revenues came from hourly billings charged for services provided to large corporate clients. The firm's partners shared ownership and governance responsibilities, and employed a large number of associate lawyers to work on client projects for salary, a few of whom would be promoted into the partnership in any given year.

Two trends in legal services have combined to increase the complexity of the work for elite law firms making the setting particularly good for studying complex work. First, as documented by Burk and

McGowan (2010: 25), clients have been shifting their routine work to in-house teams or to outsourced legal services groups. Thus, they tend to reserve complex matters for top law firms like the one we study. Second, as noted by Gardner (2014: 5), most elite law firms have focused on expertise specialization, creating narrowly defined practice areas. Thus, the collective expertise of the firm has become distributed across people, offices and practice areas, and the growing complexity of client issues means that lawyers often must collaborate with one another throughout the firm.

Like many other law firms, each lead partner in the firm controlled his or her own book of clients, with little change unless that lead partner left the firm. Each client relationship was managed by a client lead partner, typically but not always the partner who brought in the business, and could involve many unique client legal matters, which we refer to as "projects" from here onward. The knowledge network for a given client encompassed the lawyers billing hours to one of that client's projects (i.e. the lead partner and other partners). The partners working on these client projects applied knowledge from different areas of expertise or geographic jurisdictions. More complex client needs typically required involving lawyers from different knowledge domains and geographic jurisdictions as well as lawyers considered top experts in their areas. For example, the team of lawyers representing an US-based client in a patent dispute with a Chinese competitor could include partners based in multiple US and Chinese cities, and encompassing expertise in the areas of intellectual property, regulation, and litigation. The volume of partner-level work also could require the involvement of multiple partners even if their content expertise overlapped considerably. As a result, large client projects routinely included multiple partners working interdependently and overseeing associates who were also working on the same projects.

In this and other US law firms operating during the study period, there was a modest but increasing amount of lateral mobility taking place among partners who chose to move out of the firm, usually to another large law firm where they would continue doing similar work. When these partner exits took place, they were likely to disrupt the performance of client relationships for which the exiting partner was the lead partner. Hence our research examines the moderating effect that the knowledge network can have on client relationship performance following these partner exits.

To identify the knowledge networks for each client, we considered a lawyer to be part of a client knowledge network if he or she was the designated responsible lawyer for at least one project (i.e. matter) billed to that client in that year. Each project had only one designated responsible lawyer, who may or may not be the client lead partner; in cases where this person was not the client lead partner, the project's designated responsible lawyer would have to coordinate with and ultimately defer to the client lead partner. As a practical matter, lawyers who were designated responsible lawyers for projects had to have also billed at least 50 (and in most cases many more) of their own billable hours per year to the client to be considered part of the network. Using this method, if five lawyers were designated responsible lawyers for projects billed to a given client in a given year, then those five lawyers defined the knowledge network for that client in that year.[2] After composing the client knowledge networks, we then operationalized measures for the key dimensions of the networks by combining information about the co-billings of partners to client projects.

We organized our data into client-year observations. The resulting unbalanced panel encompasses 8852 clients over a maximum of ten years, for a combined total of 26,371 client-year observations (per agreement with the research site, some numerical details are withheld to preserve site anonymity).

Dependent variable

We operationalized client relationship performance using the total billable hours charged to each client in a given year. Those billings represent the sum of all partner and associate billings, and reflect a key internal short-hand for representing the relative performance of a given client account for the law firm. Total client billable hours ranged from a minimum of less than 100 to a maximum of nearly 100,000 with a mean value of roughly 500 hours per year. We used the log of total client billable hours in our analysis to ensure a normal distribution of the dependent variable.

Independent variables

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[2] In our dataset, the designated responsible lawyers were all partners in the law firm, so by definition the knowledge networks were comprised of partners. Associates also worked on the client relationships, but they did so at the direction of the partners serving as designated responsible lawyers, and their work is ultimately signed off by the partner in charge. Therefore we do not include associates in the construction of the knowledge network measures.

Lead partner exit. We coded the years after a client lead partner exited the firm, using the firm's personnel records on the entry and exit dates for all of the firm's lawyers. We also verified that the client lead partners we identified as exiting did not return in subsequent years.

Domain heterogeneity. To operationalize the heterogeneity of expertise in the knowledge network, we used a count of different departments (i.e., knowledge domains) represented in the team billing the client each year. In our context all lawyers were assigned to exactly one of eight different departmental units based on their domains of legal expertise, including corporate transactions, litigation, tax, intellectual property, labor and employment, bankruptcy, and two other minor areas (withheld to protect research site anonymity). Those assignments were very stable over time. Hence our measure for domain heterogeneity is based on the numbers of different departments represented by the lawyers in each client knowledge network (each year).

Geographic heterogeneity. We calculated geographic heterogeneity using a count of the different city office locations of those lawyers in each client knowledge network (each year). There were four different possible office locations for the lawyers used in this analysis (all located in one of the top 10 largest U.S. metropolitan statistical areas), and very little movement between the locations over time.

Expert knowledge. We calculated an expert knowledge index for each knowledge networks as follows. First, for each lawyer in the knowledge network, we generated an internal expert status score and an external expert status score. For internal expert status, we used the Eigenvector centrality of the lawyer in the firm's overall billings network in a given year. Eigenvector centrality is a measure of the popularity of an actor in a network and reflects how sought after the resources or knowledge accessible from a given actor are to others in the network (Bonacich 1972). Thus, a lawyer's internal expert status score reflects how often they are invited to join client teams and the connectedness of the teams they join. For external expert status, we used the Martindale Hubbell peer review lawyer rating system for that year, using an indicator for whether a partner was awarded "Preeminent" (2), "Distinguished" (1), or neither (0). The Martindale rating is based on surveys of other corporate lawyers who are members of the bar and judiciary (who could be in client organizations, other law firms, or serving as judges). The internal and external expert status indicators were standardized and averaged to create each lawyer's overall average expert knowledge score. We then averaged those indices across all lawyers in the knowledge network for that year to create an expert knowledge index for each client knowledge network.[3]

Cohesion. To measure cohesion, we considered two lawyers in a given knowledge network to be tied if they both billed 10 or more hours together on common projects for clients other than the focal client in a given year (ten hours was the minimum threshold set the by firm to signify non-trivial involvement in a client matter, reflected in their record-keeping system). Within each client knowledge network, lawyers could be co-billing other projects together, or they could have no overlap in project billings outside of the focal client. We used those ties as the basis for calculating knowledge network cohesion, following the standard network density formula (*observed ties*)/(*possible ties*), where *possible ties* is $n(n-1)/2$. An alternative specification using a 20-hour cut-off to define cohesion ties yields similar results to those reported below, while a 50-hour cut-off reduces significance levels for our findings.

Control variables

We include several controls to account for other sources of variance in the performance of client relationships that could confound our analysis. These include lagged logged performance in billable hours (the dependent variable), knowledge network size (lawyers per client), and the duration of the client relationship (number of years, top coded at the start of the study period). We also controlled for the lead partner's centrality in the firm's internal network, the lead partner's own hours billed to the client, and the lead partners total billings across all clients. Although the knowledge networks we study have little formal hierarchy, they do differ in the extent to which lawyers are formally assigned to collaborate on the same tasks for the client, and therefore we include a measure of the formal assignment structure of the knowledge network (defined as the assignment of partners across the set of projects within the focal client

[3] We find similar results using an alternative internal measure based on the lawyer's rank in terms of revenue generation, which is positively and significantly correlated with the lawyer's network centrality. We also obtained similar results using an indicator set to one if two or more lawyers in the network held "Preeminent" external ratings.

relationship) as a control. We also included year dummies to account for any business cycle or other common calendar year variations in the performance of all client relationships.

Analysis

Our hypotheses concern the performance effects of lead partner exits for different client relationship knowledge networks; hence a common approach to test the hypotheses would be to estimate fixed effects OLS regressions of billable-hours performance for each client relationship. However, such an approach does not account for the fact that lead partner exits are not randomly assigned. Standard OLS estimates are subject to endogeneity bias, as an omitted variable that affects both the likelihood of partner exit and client billable hours such as performance (Carnahan et al., 2012) could confound our results. To address these concerns we employ a modified version of two-stage least-squares (2SLS) regression using two instrumental variables for partner exit in the first stage: partner death or illness and lateral partner hires. Death or illness results in the exit of the partner from the client relationship, but itself does not affect the billable hours for the client relationship. Lateral partners, those partners who were previously partners at another firm, are more likely to move again within five years of their entrance to the firm (Altman Weil 2011). However, being a lateral partner does not directly affect client billable hours. Thus, both instruments satisfy two critical assumptions: they significantly predict partner exit but they do not have a direct effect on client billable hours.

Following Samila and Sorenson (2011), we estimated the instrumental variables regressions in two stages. We first regressed lead partner exit on the instruments and all independent and control variables, exactly as in the first stage of a standard 2SLS estimation. We then used the predicted partner-exit values from that model, along with the interactions of those predicted values and our independent variables, in the second stage regressions predicting client relationship performance. We adjusted coefficient standard errors in the second stage to reflect covariance across the two stages, following Baltagi (2002: 277) and Wiggins (2013). This approach avoids the "forbidden regression" concern that arises when 2SLS is applied to a nonlinear first-stage model (Angrist and Pischke 2008), and it ensures that the standard errors are correctly adjusted in the second stage. We also verified that our results remain substantively equivalent using three alternative methods: (1) bootstrapping the standard errors (1000 times) in the second stage of the regression rather than manually adjusting them; (2) instrumenting both the endogenous variable partner-exit and the interaction of the endogenous and exogenous variables with the instrument and the interaction of the instrument and the exogenous variable, following Wooldridge (2000: 236-7); and (3) following a three-step procedure suggested by Adams, Almeida and Ferreira (2009), in which we first use a Poisson fixed-effects model to predict exit using our instruments and controls, and then used predicted values from that model (instead of the instruments) in an OLS fixed-effects model predicting exit, and finally use the predicted values from that model in a second-stage regression predicting client relationship performance.

In order to assess the validity of our instruments, we ran a conventional 2SLS fixed-effects model with all of our explanatory variables and control variables, using the STATA *xtivreg2* command. The association specification tests indicate satisfactory instrument validity. Specifically, the Anderson underidentification test is high (125.7, Chi-squared $p<.001$) and the Cragg-Donald Wald F-statistic is high relative to the Stock-Yogo (2005) weak instrument critical values (126.5, $p<.001$, versus 16.4 for 10% maximal IV size). The Sargan statistic indicates over-identifying restrictions as a group are valid (3.5, $p>.05$).

We test our hypotheses using the second stage models predicting logged billable hours for each client relationship. These models all use OLS regressions, with the first-stage predicted value for lead partner exit included. The models also all include client fixed effects, generated using Stata's *xtreg, fe,* and also include year dummies. The fixed effects control for variation across clients, and isolate the analysis to explain variation in each client's performance over time. Note also that up until the time of exit, the client lead partner is constant for all observations, so the client fixed effects models also effectively control for variance across client lead partners that could affect both characteristics of the networks and the client relationship performance. All independent variables are lagged (t-1). A failed Arellano-Bond AR(2) test using Stata's *xtabond2* does not support the inclusion of additional endogenous-variable lags. Finally, we checked for multicollinearity concerns by repeated our analyses using ordinary least squares (OLS) regressions; variance inflation factor (VIF) values all fall below 3.0, except for Lawyers Per Client (having a value of 3.21). The overall mean VIF was 1.44, well below the common threshold of 5.

RESULTS

Descriptive statistics and correlations are presented in Table 1 (based on pooled client-year observations). The first stage model estimates are reported in Model 1 of Table 2. Both of the instruments, lateral partner and death or illness, are significant predictors of lead partner exit. As noted above, they also satisfy a critical assumption for instrumental variables in that they do not directly affect client relationship performance.[4] From the first stage model, we generated a predicted probability of exit which is included in the second stage models reported in Table 3. Model 2 of Table 2 reports the results of a client fixed-effects regression analysis without the endogeneity correction showing that exits of lead partners have a significant negative effect ($p<0.001$) on the performance of client relationships. However, as noted above, lead partner exits are not randomly assigned, and so in Table 3 we report estimates from two-stage instrumental variables regressions.

Our first hypothesis is that the (negative) effect of lead partner exit will be greater when the knowledge network has higher heterogeneity. The results of Model 2 in Table 3 provide support for Hypothesis 1a; the coefficient for *lead partner exit * domain heterogeneity* is negative and significant ($p<.001$). Hypothesis 1b predicting that the effect of lead partner exit would also be more negative for more geographically heterogeneous knowledge networks also was supported ($p<.05$) as indicated in Model 3 of Table 3. The moderation effects of domain heterogeneity and geographic heterogeneity on the relationship between lead partner exit and performance are presented graphically in Figures 1 and 2. The graphs illustrate two interesting points. First, client relationships with high knowledge heterogeneity

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[4] The lack of a direct effect of lead partner death or illness on client performance is probably due to a basic difference in the reactions of clients to partners who leave the firm willingly versus partners who leave due to death or serious illness. In the former case, the partner is nearly always moving to a competing law firm, and the client has an incentive to move some of its business to the new firm in order continue benefitting from the human capital and external social capital of the partner, which reduces client tie performance. In contrast, for a death/illness partner exit, that human capital and external social capital are gone no matter what the client does, and so, clients are not significantly more likely to reduce their business following these exits.

networks have higher performance than client relationships with low knowledge heterogeneity networks when there are no lead partner exits. Second, while exit has a negative effect for all levels of knowledge heterogeneity, the effect is greater for higher levels of heterogeneity (one standard deviation above the mean) and networks with high heterogeneity actually perform at lower levels than low heterogeneity networks when the lead partner exits.

Hypothesis 2 proposed that the (negative) effects of lead partner exit on client relationship performance will be greater when there are multiple experts in the knowledge network. The results in Model 4 of Table 3 provide support for Hypothesis 2, with a negative and significant ($p<.001$) coefficient for the interaction term *lead partner exit * expert knowledge*. Figure 3 shows this moderating effect graphically: multiple experts is associated with higher performance when there are no exits; but the negative post-exit performance effect becomes even more steeply negative for those clients with high expert knowledge (i.e. multiple experts) in the knowledge network.

Hypothesis 3 proposed that the (negative) effects of lead partner exit on client relationship performance would be lower when there is greater cohesion in the knowledge network. The results in Model 5 in Table 3 show that cohesion significantly affects the impact of lead partner exit on performance as predicted ($p<.01$). Figure 4 plots this result, indicating that high network cohesion is associated with higher performance and that greater cohesion reduces the negative impact of partner exit. Model 6 includes all of the two way interaction terms that were significant in prior models and the pattern of results remains the same. However, the interaction of geographic heterogeneity and exit loses significance.

Hypothesis 4 predicted that the increase in the negative performance effect of lead partner exit when knowledge heterogeneity or expert knowledge is high would be lower the greater the cohesion in the knowledge network. Table 4 provides partial support for the hypothesis. For high knowledge heterogeneity (i.e. domain heterogeneity and geographic heterogeneity), network cohesion reduces the negative performance impact of lead partner exit ($p<0.05$ and $p<0.001$ respectively), supporting H4a and H4b. However, we do not find a significant interaction effect of network cohesion with expert knowledge when the lead partner exits and thus H4c is not supported. As illustrated in Figure 5, the highest performance when no exits occur is when the network has high domain heterogeneity and high cohesion. But for client relationships experiencing the exit of a lead partner, the performance benefits of high domain heterogeneity are lost, and client knowledge networks with low cohesion and high domain heterogeneity have the lowest performance when the lead partner exits. Figure 6 plots the performance effects of cohesion and geographic heterogeneity for lead partner exits. More cohesive networks are associated with high performance for knowledge networks of high or low geographic heterogeneity when there are no exits. However, if the lead partner exits, knowledge networks with high geographic heterogeneity perform worse than low geographic heterogeneity and the drop is even greater if the network has low cohesion.

In order to consider the practical magnitude of these effects, we assume an average hourly bill rate of $500 for the (unlogged) total billable hours per client. Because our regression models control for the previous year's total billable hours and include client fixed effects, the results represent effects on the net change (growth) in client billable hours from one year to the next. Based on the levels used in Figure 1, we find that at high levels of domain heterogeneity (one standard deviation above the mean), the effect of partner exit on year-over-year client revenue growth is a decline from $28,130 ($500*e^{4.0}$) to $3,769 ($500*e^{2.0}$), or -77%. In contrast, at low levels of domain heterogeneity (one standard deviation below the mean), partner exit lowers client revenue growth from $13,421 ($500*e^{3.3}$) to $7,007 ($500*e^{2.6}$), a change of only -48%. At high levels of geographic heterogeneity as shown in Figure 2, following lead partner exits, revenue growth decreases from $20,224 to $5,679 (-72%). At low levels of geographic heterogeneity the decrease is smaller, from $17,406 to $6,937 (-60%). For the effects of expert knowledge shown in Figure 3, lead partner exit affects client knowledge networks with multiple experts by slowing revenue growth from $28,310 to $4,292 (-85%), while for lower levels of expert knowledge, revenue growth drops from $12,640 to $8,819 (-30%). Finally, the effects of cohesion shown in Figure 4 indicate that under low cohesion, revenue growth slows from $13,556 to $3,884 (-71%); while under high cohesion, revenue growth only slows from $25,967 to $13,025 (-50%).

Regarding the three way interaction effects, the magnitude of the effect of exit shown in Figure 5 when both domain heterogeneity and network cohesion are high is large. Revenue growth slows by 77% from \$35,405 to \$8,141. However, when domain heterogeneity is high and network cohesion is low, the size of the effect is even greater. Revenue growth drops by 93% from \$20,224 to \$1,502. For geographic heterogeneity, the buffering effect of network cohesion is also large. As shown in Figure 6, when both geographic heterogeneity and network cohesion are high, revenue growth drops 29% from \$26,492 to \$18,856. In contrast, when geographic heterogeneity is high and network cohesion is low, revenue growth drops 84% from \$13,025 to \$2,132.

Additional analyses and robustness checks. We replicated our analyses using two alternative measures of domain heterogeneity and geographic heterogeneity. First, we constructed two Blau (1977) diversity index measures to represent the weighted distribution of departments and office locations represented in the knowledge network. The Blau index is:

$$B = 1 - \sum_{i=1}^{k} p_i^2$$

where P_i is the proportion of group members in category i, and k is the number of possible categories. The measure ranges from zero, indicating no diversity, to a maximum of $(k - 1)/k$, where k is 8 for departments and 4 for office locations. Results are displayed in Supplemental Tables S1 and S2. The results closely track those we reported above for knowledge heterogeneity based on the simple count of departments and office locations. The three way interaction results are also similar, except that the interaction of lead partner exit, geographic heterogeneity and network cohesion is not significant. We also obtained the same pattern of consistent results using a second alternative measure, the Index of Qualitative Variation (Agresti and Agresti 1978), which is similar to a Blau index adjusted for group size.

We also replicated our analyses of the effects of multiple experts in a sample that excluded clients whose lead partner was a knowledge expert. The results were qualitatively similar to those presented in Table 3. We also tested the knowledge network effects separately for partners exiting within five years of the firm's mandatory retirement age, versus other partner exits. Partners planning for imminent retirement may manage succession for their clients in a way that reduces the impact of knowledge network characteristics on post-exit client performance. Interacting each type of exit (near-retirement and other) with the knowledge network characteristics, we find the interaction coefficients are generally smaller for the near-retirement exit type, but the coefficients do not significantly differ for the two types of exits. However, this result may be due to limited statistical power given the small number of partners exiting near retirement age in our data.

The mechanism we proposed for the increase in the performance loss following a lead partner departure is coordination by the lead partner. Yet, we were not able to directly observe lead partners' coordination behaviors. Therefore, we ran an additional check of our coordination mechanism by investigating how our effects changed for lead partners with responsibility for a larger number of active clients, whose capacity for coordination knowledge networks would be correspondingly diminished. To explore this, we replicated our regressions for lead partners with a greater-than-average number of active clients (logged values over 3.67), and for lead partners with lower-than-average active clients (logged values of 3.67 or below). Focusing on the heterogeneity and experts knowledge interactions, we find results of similar or greater significance for the lower-than-average group, compared with the results reported in Table 4. In comparison, results for the greater-than-average group were reduced in significance. This pattern of results is consistent with our argument that lead partners play an important coordinating role for complex knowledge networks, as the effects diminish when lead partners lack the capacity to engage in extensive coordination behavior (due to overseeing many clients) and increase when they have better capacity for coordination (due to overseeing only a few clients).

Our main models use one-year lags for our independent variables because we expect the coordination losses associated with the departure of the lead partner to occur immediately. In an effort to see how client ties perform over the years following employee departure, we extended the lags for all independent variables to two years. As expected, in the saturated model, the post-exit effects of knowledge heterogeneity fall below statistical significance, as does the post-exit effect of cohesion. The post-exit effect of multiple experts remains significant. Further extending the lags to three or more years reduces the significance of the post-exit interaction effects. The reduced effects are likely to be a result of the introduction of greater noise arising from more unobserved events occurring in the intervening years introduced by the longer lags. However, the pattern of results suggests that there is an immediate effect of partner exit and that this effect is greater for networks high in heterogeneity and expert knowledge, and lower for networks that are high in cohesion as hypothesized.

Finally, the main results are also robust to the omission of the endogeneity correction.

DISCUSSION AND CONCLUSIONS

Manager mobility is costly for firms. Yet as we have argued and shown here, the costs depend in part on the knowledge networks assembled to serve clients. As the complexity of a knowledge network increases, the importance of the lead partner as a coordinator of knowledge also rises, and the loss of that lead partner becomes more costly. Our study provides a new vantage point for manager mobility, and the inter-organizational ties literature in general, by offering a knowledge network perspective. The network that is "left behind" is as important as the manager's mobility event in shaping performance outcomes. This argument is supported by an analysis of client relationships of a large law firm. As networks include more heterogeneous knowledge and involve multiple experts, the performance cost of lead partner exit rises significantly. In contrast, greater cohesion of the knowledge network significantly decreases the cost of lead partner exit. Cohesion also interacts with knowledge heterogeneity, attenuating the negative effect of partner exit on performance when knowledge heterogeneity is high. Furthermore, these findings were produced using a method of analysis that rules out confounding factors related to any differences between clients, between lead partners, and between calendar years, and which adjusts for the likelihood of the exit of the lead partner.

The pattern of findings is consistent with the idea that firms face a performance trade-off in the organization of their exchange relationships (cf. Baker 1990, Rogan 2014b). The highest performance in client relationships was achieved when the heterogeneity of the knowledge network was greatest--yet those particular knowledge networks experienced much greater performance drops following the exit of the lead partner, in many instances to levels below those of the less-heterogeneous knowledge networks.

Thus, in the near term (no exit events), the optimal structure of an exchange relationship is a heterogeneous knowledge network, but in the long term (if and when exits events are going to occur), a lower-heterogeneity knowledge network in which the lead partner plays a minimal role may be preferable in order to avoid the greater post-departure performance losses.

Our findings also offer implications for research into the advantages and disadvantages of cohesion for performance. In prior research, cohesion has been associated with redundant information and constraint. Therefore it has been viewed as a limiting factor in innovation, i.e. in creative work that depends on access to novel information. However, this view may oversimplify the effect of cohesion on innovation. Recent research has begun to identify the conditions under which cohesion can be beneficial for innovation (Carnabuci and Operti 2013, Guler and Nerkar 2012). Innovation often involves novel combinations of knowledge similar to the complex work we observed in our law firm setting. To the extent that innovative work is complex, the findings of our study suggest that cohesion is an important coordination mechanism for innovative work rather than a limiting factor. As we argue and show here, it reduces the firm's dependence on individual brokers for coordination of knowledge.

To be sure, our findings have scope conditions and limitations. A benefit of our study setting is that it afforded access to fine-grained primary data from a law firm. Although the law firm we studied was fairly representative of other large US-based law firms, and the findings should therefore generalize across this population, we do not know whether the findings generalize, especially outside of the US context and outside of the legal services sector. For example, in less individualistic national-culture contexts, the role of the lead partner as a coordinator could be lower. We expect that such differences would be captured by the cohesion of the knowledge network in our theory. Yet, organizations also vary in the strength of collaboration norms, which can affect the social desirability of forming boundary crossing ties (Srivastava and Banaji 2011). Our study was conducted within a single firm, which effectively held organizational culture constant; and so, some limits to generalizability of our findings across cultures, including organizational cultures, may remain. Nevertheless, the use of knowledge networks to serve clients is similar in most professional service firms such as consulting firms, advertising agencies and investment banks, and so we expect the findings to generalize to firms in those populations as well. We also expect that the knowledge network characteristics we studied would be salient in non-professional service firm settings where knowledge needs to be combined to conduct complex project work and where a group leader coordinates the knowledge, such as R&D or product development units of firms.

Some modeling limitations in our study can be improved in future work as well. We observe knowledge network conditions that are associated with work complexity; future studies might directly measure objective or perceived complexity. Furthermore, although we were careful to control for the endogeneity of lead partner exits, it remains possible that changes in billable hours actually cause changes in knowledge networks and lead partner exits. Our use of panel data with lagged independent variables greatly reduces this concern. Nevertheless, to fully address reverse causality concerns future research should seek settings with exogenous shocks to knowledge networks and manager exits, such as the loss of an entire office by a firm following a natural disaster or other unexpected event.

Our study provides contributions in three areas. The main contribution is to extend research on managerial mobility (Bermiss and Murmann 2014, Broschak 2004, Carnahan et al. 2012, Dokko and Rosenkopf 2010, Somaya et al. 2008) by providing arguments and support for the important moderating role of the internal knowledge networks maintained by managers on the relationship between the departure of these managers and relationship performance. Prior research has illuminated how characteristics of the lead manager impact performance, including the retention of relationships (e.g., Broschak 2004). We show that characteristics of the knowledge network in the focal organization which affect the need to coordinate that network impact performance as well. Our study offers a more nuanced explanation for why the losses of top executives whose functional roles are internally facing were more detrimental for the survival of firms than losses of executives maintaining external exchange relationships as documented in prior work (Bermiss and Murmann 2014). This study also connects to recent research examining how knowledge is embodied in individuals and organizational units and how the movement of executives across these affects performance (Groysberg, Lee and Nanda 2008, Karim and Williams 2012, Summers, Humphrey and Ferris 2012). While executives may transfer routines with them when they move, their departures also disrupt routines in the organizational units they depart.

Second, the arguments and findings of our study extend understanding of the fundamental trade-offs that firms face in organization design (Eisenhardt et al. 2010, Krestchmer and Puranam 2008, Lawrence and Lorsch 1967). Ironically, we find that although knowledge heterogeneity was associated with high performance before a law firm partner's departure, it was also associated with the lowest performance post-departure. Thus, professional service firms face a dilemma between encouraging the development of knowledge networks that deliver the greatest value to the firm when partner mobility is low - and protecting the firm from performance declines associated with such networks when mobility is high. Although we focused on complexity arising from external, client demands, future research could explore the potential for the firm's strategic choice in shaping project knowledge complexity.

Third, our findings also have important implications for research on complexity and network dynamics. In particular, we find that more heterogeneous knowledge networks of experts support performance when the lead partner is stable, but they become liabilities for performance when the lead partner is lost by the firm. The types of networks that enable the completion of complex work increase the need for coordination, and so, complex work effectively increases the vulnerability of the firm to the loss of coordinating brokers, i.e. lead partners in our setting. Indeed the importance of a central coordinating hub in the knowledge networks that we observed is similar to patterns in other types of networks, such as cellular networks and ecological networks (Csermely et al. 2013). The coordinating role of hubs in such networks should be relevant to organizations research into areas such as top management teams (e.g., Bermiss and Murmann 2014, Hambrick and Mason 1984) and innovation teams (e.g., Grigoriou and Rothaermel 2013, Taylor and Greve 2006), where those characteristics of the knowledge network that are optimal for performance when the lead individual (CEO or team leader) is present may become detrimental when that individual is lost. Our study also highlighted the important function played by cohesion for reducing the negative performance effects of leader departures. A question for future work is whether this trade-off can also be overcome, for example through the use of formalized routines or knowledge codification procedures that minimize the scope for disruption from the loss of a central coordinator of knowledge (see Briscoe 2007).

Finally, this research has implications for the management of professional service firms. Increasingly, work in professional service firms involves multidisciplinary and geographically dispersed client projects connecting relatively autonomous individual professionals. The effective management of such projects presents a significant challenge, even when the project membership and leadership is stable (Haas and Hansen 2005, Hitt, Bierman, Shimizu and Kochhar 2001, Løwendahl 2005). Our research suggests that an important factor in composing and managing these client projects is an awareness that increasing project complexity risks magnifying losses from the exit of key coordinating individuals. Firms may prefer to avoid the increased dependence on key coordinators (and reduced firm bargaining power) that complexity entails. Hence they might consider policies aimed at mitigating or even minimizing the types of complexity we found problematic. At the same time, doing so is likely to create other costs for firms, such as foregoing potentially lucrative but complex client projects.

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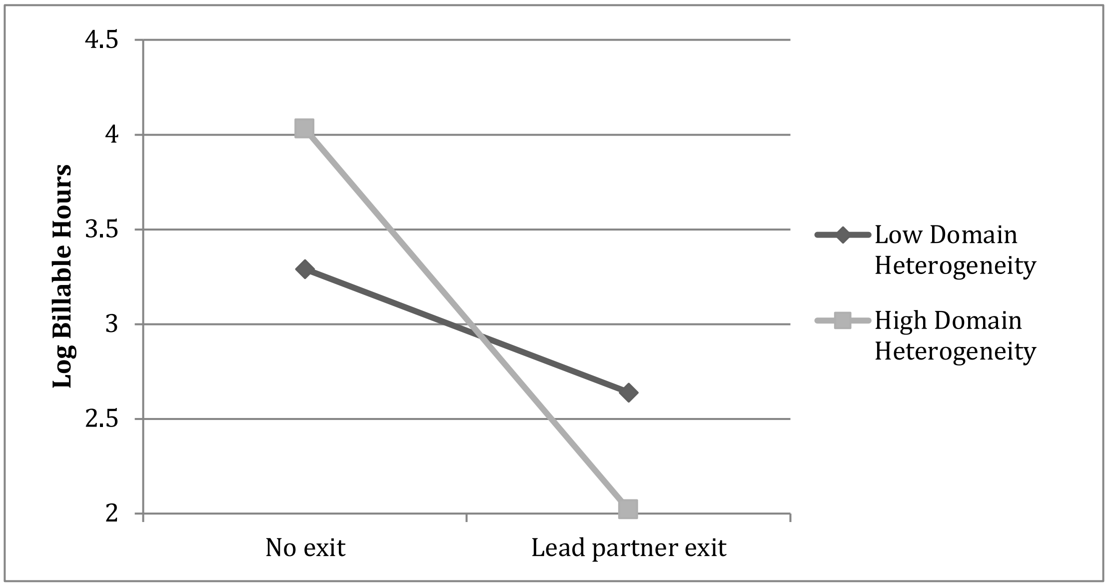
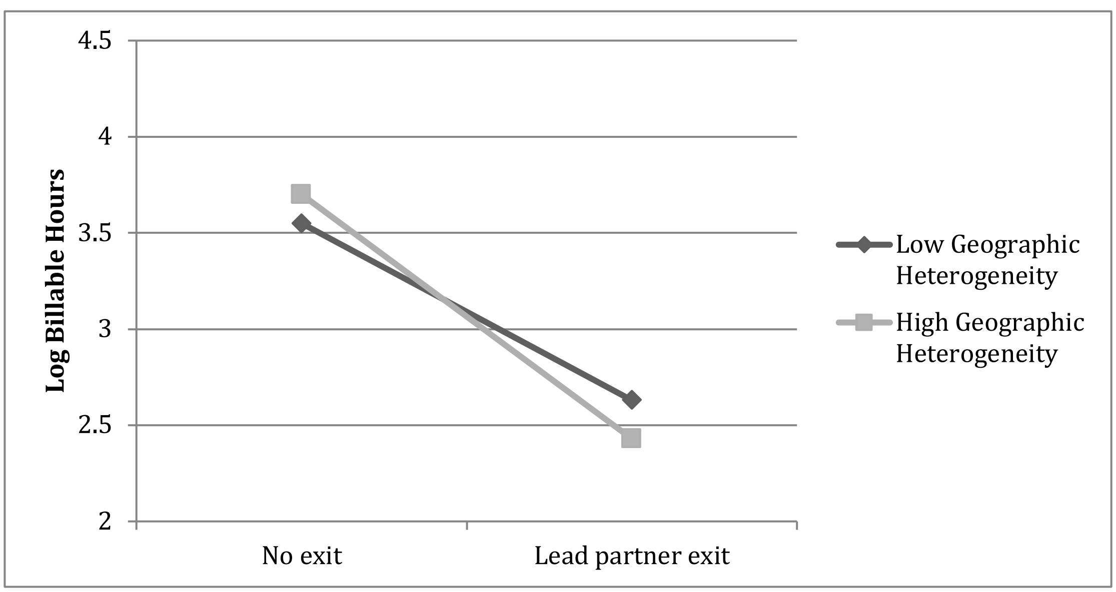
Figure 1: Predicted client relationship performance (log billable hours) resulting from the interaction of lead partner exit and knowledge domain heterogeneity



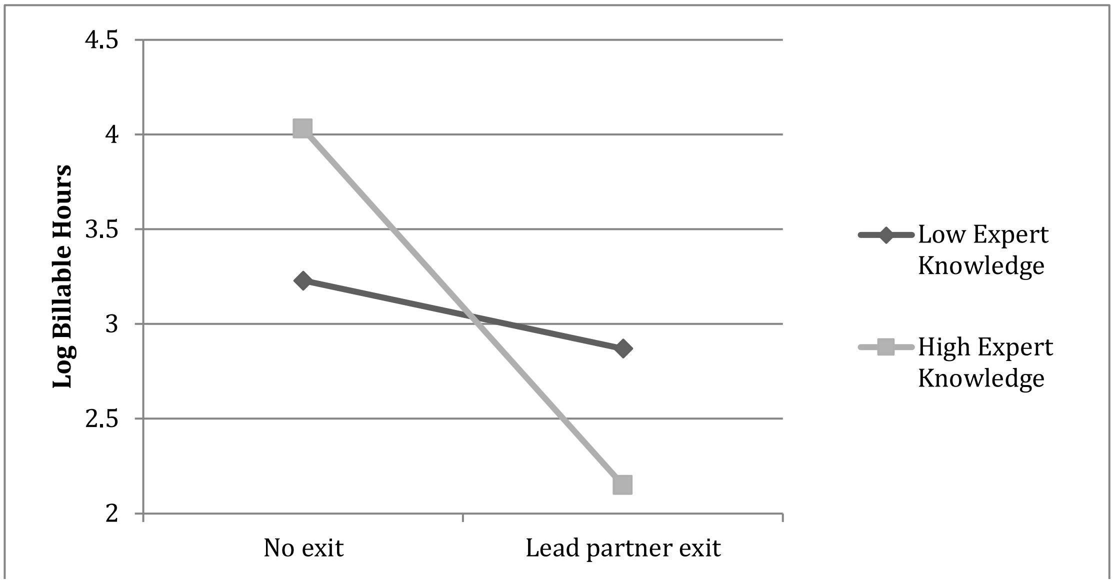
The graph is generated using the estimated from Model 2 in Table 3. All covariates are at their means, except for partner exit, which is set to 1 for the time period post exit, and domain heterogeneity which varies from one standard deviation below to one standard deviation above the mean.

Figure 2: Predicted client relationship performance (billable hours) resulting from the interaction of lead partner exit and geographic knowledge heterogeneity



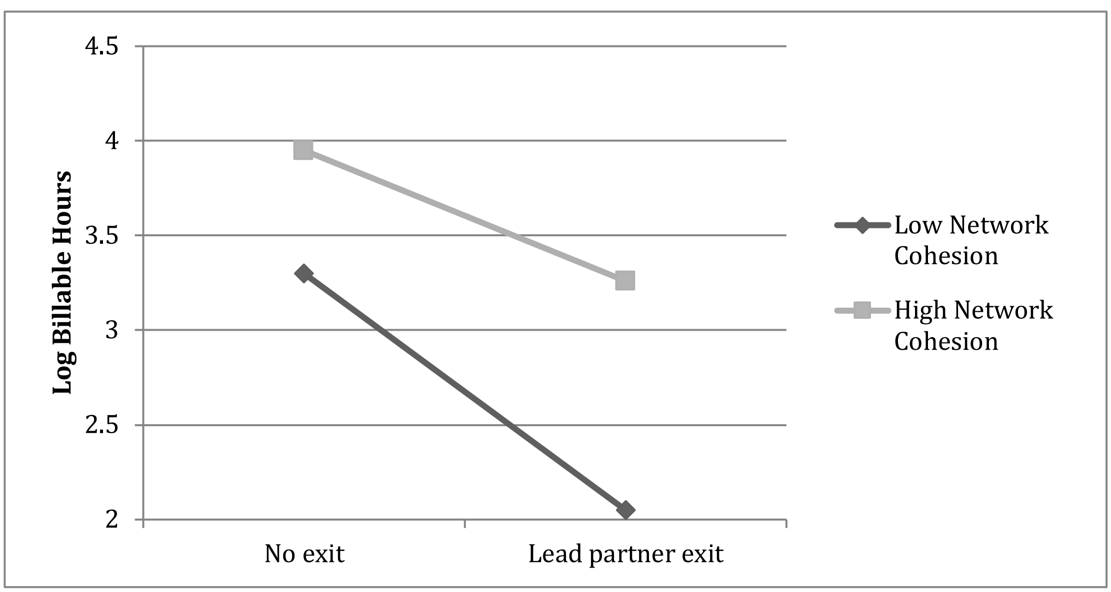
The graph is generated using the estimated from Model 3 in Table 3. All covariates are at their means, except for partner exit, which is set to 1 for the time period post exit, and geographic heterogeneity which varies from one standard deviation below to one standard deviation above the mean.

Figure 3: Predicted client relationship performance (billable hours) resulting from the interaction of lead partner exit and expert knowledge



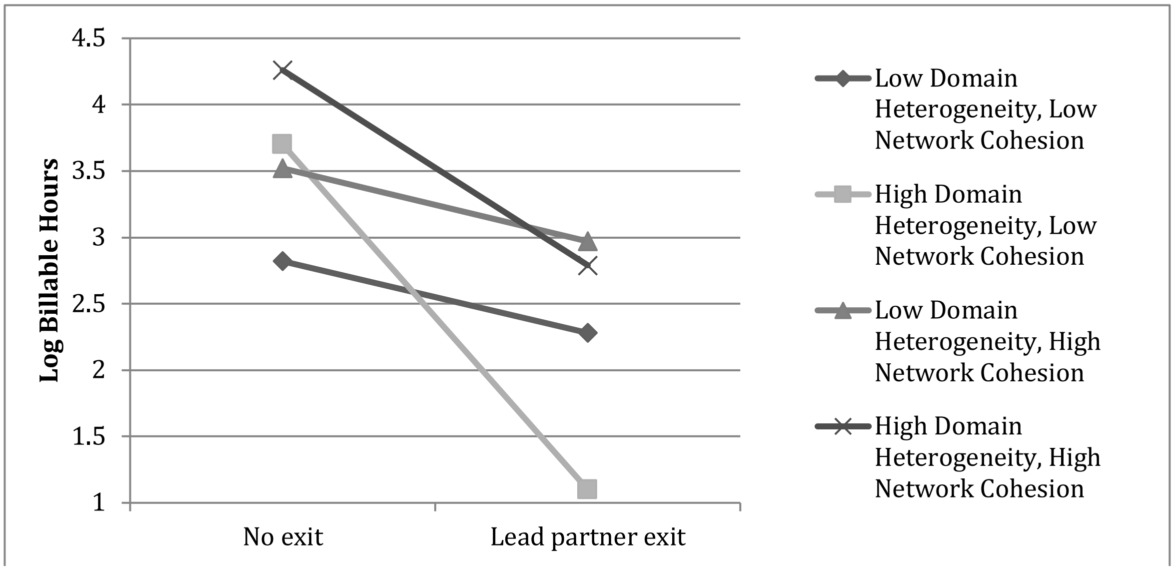
The graph is generated using the estimated from Model 4 in Table 3. All covariates are at their means, except for partner exit, which is set to 1 for the time period post exit, and expert knowledge which varies from one standard deviation below to one standard deviation above the mean.

Figure 4: Predicted client relationship performance (billable hours) resulting from the interaction of lead partner exit and cohesion



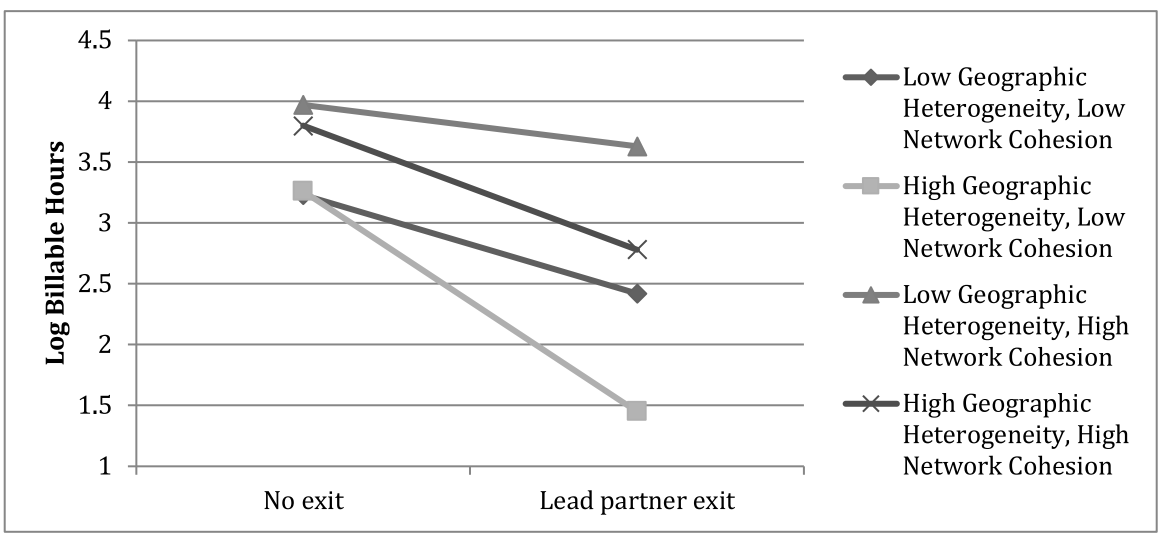
The graph is generated using the estimated from Model 5 in Table 3. All covariates are at their means, except for partner exit, which is set to 1 for the time period post exit, and cohesion which varies from one standard deviation below to one standard deviation above the mean.

Figure 5: Predicted client relationship performance (billable hours) resulting from the interaction of lead partner exit, cohesion, and knowledge domain heterogeneity



The graph is generated using the estimated from Model 1 in Table 4. All covariates are at their means, except for partner exit, which is set to 1 for the time period post exit, cohesion and domain heterogeneity which vary from one standard deviation below to one standard deviation above the mean.

Figure 6: Predicted client relationship performance (billable hours) resulting from the interaction of lead partner exit, cohesion, and geographic knowledge heterogeneity



The graph is generated using the estimated from Model 2 in Table 4. All covariates are at their means, except for partner exit, which is set to 1 for the time period post exit, cohesion and geographic heterogeneity which vary from one standard deviation below to one standard deviation above the mean.

Table 1: Descriptive statistics and correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Log Performance	3.57	2.98													
2. Lawyers per Client	6.53	21.35	.34												
3. Client Tie Duration	4.04	3.43	.23	0.13											
4. Lead Partner Centrality	.20	0.15	.05	.06	.32										
5. Lead Partner Billings to Client	.46	2.04	.38	.80	.10	.03									
6. Formal Assignment Structure	.09	.21	-.39	-.03	-.20	-.32	-.04								
7. Lead Partner Total Billings	7.82	21.71	.09	.09	.08	.19	.09	-.04							
8. Domain Heterogeneity	1.18	.57	.29	.40	.19	.11	.30	-.08	.00						
9. Geographic Heterogeneity	1.01	.24	.16	.25	.11	.11	.22	-.05	.04	.40					
10. Expert Knowledge	2.80	.47	.19	.06	-.01	.12	.07	-.12	.20	-.04	.04				
11. Network Cohesion	.26	.36	.28	.06	-.01	.02	.02	-.05	.03	.03	.00	.06			
12. Lead Partner Exit	.02	.14	-.06	-.04	.25	-.05	-.03	-.03	-.05	.02	.06	-.04	-.09		
13. Laternal Partner	.01	.11	-.01	-.02	.06	-.01	-.02	-.02	-.03	-.06	-.09	.01	-.02	.33	
14. Death or Illness	.01	.01	.00	.00	.01	.01	.00	-.01	.00	-.01	-.01	.01	.00	.09	.00

Table 2: Effect of actual client lead partner exit on client relationship performance and first-stage model predicting exit

	Model 1 *Lead Partner Exit*	Model 2 *Client Relationship Performance*
Log Performance (t-1)	-0.007***	0.473***
	(0.000)	(0.008)
Lawyers per Client	0.000	-0.016***
	(0.000)	(0.001)
Client Relationship Duration	0.013***	0.062***
	(0.000)	(0.004)
Lead Partner Centrality	-0.268***	-3.114***
	(0.009)	(0.108)
Lead Partner Billings to Client	0.001	0.392***
	(0.001)	(0.011)
Lead Partner Total Billings	-0.000**	0.002***
	(0.000)	(0.001)
Formal Assignment Structure	-0.004	-4.793***
	(0.004)	(0.065)
Domain Heterogeneity	0.012***	0.589***
	(0.002)	(0.027)
Geographic Heterogeneity	0.010***	0.188***
	(0.004)	(0.061)
Expert Knowledge	0.002	0.705***
	(0.002)	(0.029)
Network Cohesion	0.001	1.033***
	(0.002)	(0.040)
Lead Partner Exit (actual)		-0.518***
		(0.100)
Lateral Partner	0.237***	
	(0.021)	
Death or Illness	0.376***	
	(0.006)	
Client fixed effects	Y	Y
Year dummies	Y	Y
Observations	26371	26371
Number of clients	8852	8852
R-squared	.117	.271

Standard errors in parentheses
***p<0.001, ** p<0.05, * p<0.10

Table 3: Instrumental variables estimates of client relationship performance, with client and year fixed-effects

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log Performance (t-1)	0.026	0.022	0.025	0.026	0.025	0.019
	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.020)
Lawyers per Client	-0.008***	-0.007***	-0.008***	-0.007***	-0.008***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Client Relationship Duration	-0.061**	-0.050*	-0.060**	-0.061**	-0.065**	-0.052*
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.031)
Lead Partner Centrality	-1.865***	-2.090***	-1.896***	-1.873***	-1.801***	-2.038***
	(0.618)	(0.603)	(0.608)	(0.614)	(0.620)	(0.647)
Lead Partner Billings to Client	0.392***	0.394***	0.393***	0.391***	0.392***	0.394***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Lead Partner Total Billings	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Formal Assignment Structure	-5.497***	-5.496***	-5.496***	-5.476***	-5.500***	-5.479***
	(0.087)	(0.084)	(0.085)	(0.086)	(0.087)	(0.090)
Domain Heterogeneity	0.570***	0.771***	0.574***	0.567***	0.566***	0.774***
	(0.049)	(0.059)	(0.048)	(0.048)	(0.049)	(0.064)
Geographic Heterogeneity	0.229**	0.259***	0.326***	0.240***	0.227**	0.273**
	(0.090)	(0.088)	(0.103)	(0.089)	(0.090)	(0.110)
Expert Knowledge	0.751***	0.751***	0.751***	0.835***	0.752***	0.841***
	(0.041)	(0.040)	(0.040)	(0.043)	(0.041)	(0.045)
Network Cohesion	0.945***	0.951***	0.946***	0.944***	0.905***	0.903***
	(0.050)	(0.048)	(0.049)	(0.049)	(0.054)	(0.056)
Predicted Lead Partner Exit	-2.719	0.671	-0.818	8.264***	-2.938	12.407***
	(2.131)	(2.156)	(2.336)	(2.860)	(2.139)	(3.232)
Lead Partner Exit X Domain Heterogeneity		-3.411***				-3.592***
		(0.586)				(0.659)
Lead Partner Exit X Geographic Heterogeneity			-1.914*			-0.039
			(1.039)			(1.157)
Lead Partner Exit X Expert Knowledge				-3.937***		-4.220***
				(0.689)		(0.725)
Lead Partner Exit X Network Cohesion					1.906**	2.227**
					(0.934)	(0.973)

Client fixed effects?	Y	Y	Y	Y	Y	Y
Year dummies?	Y	Y	Y	Y	Y	Y
Observations	26371	26371	26371	26371	26371	26371
Number of clients	8852	8852	8852	8852	8852	8852
R-squared	.30	.30	.30	.30	.30	.31

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 4: Instrumental variables estimates of client relationship performance, with client and year fixed-effects: Interactions with network cohesion

	Model 1	Model 2	Model 3
Log Performance (t-1)	0.020	0.024	0.024
	(0.018)	(0.018)	(0.019)
Lawyers per Client	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)
Client Relationship Duration	-0.052*	-0.064**	-0.064**
	(0.029)	(0.029)	(0.029)
Lead Partner Centrality	-2.051***	-1.822***	-1.802***
	(0.603)	(0.601)	(0.615)
Lead Partner Billings to Client	0.395***	0.394***	0.392***
	(0.012)	(0.012)	(0.012)
Lead Partner Total Billings	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
Formal Assignment Structure	-5.500***	-5.496***	-5.480***
	(0.084)	(0.084)	(0.086)
Domain Heterogeneity	0.763***	0.562***	0.563***
	(0.059)	(0.047)	(0.048)
Geographic Heterogeneity	0.258***	0.287***	0.239***
	(0.088)	(0.102)	(0.090)
Expert Knowledge	0.752***	0.750***	0.838***
	(0.040)	(0.040)	(0.043)
Network Cohesion	0.908***	0.909***	0.898***
	(0.052)	(0.052)	(0.053)
Predicted Lead Partner Exit	0.931	1.364	8.413***
	(2.173)	(2.346)	(3.064)
Lead Partner Exit X Domain Heterogeneity	-3.905***		
	(0.650)		
Lead Partner Exit X Geographic Heterogeneity		-4.311***	
		(1.105)	
Lead Partner Exit X Expert Knowledge			-4.083***
			(0.804)
Lead Partner Exit X Network Cohesion	-0.759	-13.488***	1.411
	(1.819)	(2.701)	(4.908)
Lead Partner Exit X Domain Heterogeneity X Cohesion	2.310*		

	(1.349)		
Lead Partner Exit X Geographic Heterogeneity X Cohesion		15.669***	
		(2.599)	
Lead Partner Exit X Expert Knowledge X Cohesion			0.273
			(1.721)
Client fixed effects	Y	Y	Y
Year dummies	Y	Y	Y
Observations	26371	26371	26371
Number of clients	8852	8852	8852
R-squared	.30	.30	.30

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S1: Instrumental variables estimates of client relationship performance, with client and year fixed-effects (Blau diversity indices)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log Performance (t-1)	0.030	0.026	0.028	0.029	0.029	0.024
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Lawyers per Client	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Client Relationship Duration	-0.053*	-0.044	-0.050*	-0.052*	-0.056*	-0.046
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Lead Partner Centrality	-1.882***	-2.071***	-1.960***	-1.897***	-1.826***	-2.036***
	(0.622)	(0.623)	(0.624)	(0.615)	(0.624)	(0.618)
Lead Partner Billings to Client	0.396***	0.398***	0.396***	0.396***	0.397***	0.398***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)
Lead Partner Total Billings	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Formal Assignment Structure	-5.520***	-5.518***	-5.520***	-5.501***	-5.523***	-5.502***
	(0.087)	(0.087)	(0.087)	(0.086)	(0.087)	(0.086)
Domain Heterogeneity	0.772***	1.093***	0.782***	0.782***	0.766***	1.096***
	(0.098)	(0.122)	(0.098)	(0.097)	(0.098)	(0.122)
Geographic Heterogeneity	0.650***	0.658***	0.816***	0.644***	0.649***	0.694***
	(0.148)	(0.148)	(0.172)	(0.146)	(0.148)	(0.171)
Expert Knowledge	0.741***	0.743***	0.742***	0.825***	0.742***	0.829***
	(0.041)	(0.041)	(0.041)	(0.043)	(0.041)	(0.043)
Network Cohesion	0.925***	0.928***	0.925***	0.924***	0.889***	0.882***
	(0.050)	(0.050)	(0.050)	(0.049)	(0.054)	(0.053)
Predicted Lead Partner Exit	-2.838	-2.763	-2.866	7.949***	-3.029	8.013***
	(2.149)	(2.146)	(2.150)	(2.852)	(2.157)	(2.851)
Lead Partner Exit X Domain Heterogeneity		-6.083***				-6.044***
		(1.383)				(1.434)
Lead Partner Exit X Geographic Heterogeneity			-3.606*			-0.921
			(1.894)			(1.960)
Lead Partner Exit X Expert Knowledge				-3.869***		-3.952***
				(0.683)		(0.683)
Lead Partner Exit X Network Cohesion					1.663*	2.056**
					(0.923)	(0.912)

Client fixed effects?	Y	Y	Y	Y	Y	Y
Year dummies?	Y	Y	Y	Y	Y	Y
Observations	26371	26371	26371	26371	26371	26371
Number of clients	8852	8852	8852	8852	8852	8852
R-squared	.30	.30	.30	.30	.30	.31

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S2: Instrumental variables estimates of client relationship performance, with client and year fixed-effects: Interactions with network cohesion (Blau diversity indices)

	Model 1	Model 2	Model 3
Log Performance (t-1)	0.025	0.027	0.028
	(0.019)	(0.019)	(0.019)
Lawyers per Client	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)
Client Relationship Duration	-0.049	-0.053*	-0.056*
	(0.030)	(0.030)	(0.030)
Lead Partner Centrality	-1.974***	-1.905***	-1.835***
	(0.626)	(0.626)	(0.617)
Lead Partner Billings to Client	0.398***	0.397***	0.396***
	(0.013)	(0.013)	(0.012)
Lead Partner Total Billings	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
Formal Assignment Structure	-5.522***	-5.523***	-5.504***
	(0.087)	(0.087)	(0.086)
Domain Heterogeneity	1.091***	0.776***	0.775***
	(0.122)	(0.098)	(0.097)
Geographic Heterogeneity	0.665***	0.813***	0.643***
	(0.148)	(0.172)	(0.147)
Expert Knowledge	0.743***	0.742***	0.828***
	(0.041)	(0.041)	(0.043)
Network Cohesion	0.887***	0.889***	0.884***
	(0.054)	(0.054)	(0.053)
Predicted Lead Partner Exit	-3.012	-3.053	8.260***
	(2.155)	(2.157)	(3.057)
Lead Partner Exit X Domain Heterogeneity	-5.163***		
	(1.474)		
Lead Partner Exit X Geographic Heterogeneity		-3.598*	
		(1.967)	
Lead Partner Exit X Expert Knowledge			-4.065***
			(0.797)
Lead Partner Exit X Network Cohesion	-0.746	1.627*	0.405
	(1.027)	(0.970)	(4.837)
Lead Partner Exit X Domain Heterogeneity X Cohesion	4.518**		

	(2.196)		
Lead Partner Exit X Geographic Heterogeneity X Cohesion		0.156	
		(2.810)	
Lead Partner Exit X Expert Knowledge X Cohesion			0.536
			(1.693)
Client fixed effects	Y	Y	Y
Year dummies	Y	Y	Y
Observations	26371	26371	26371
Number of clients	8852	8852	8852
R-squared	.30	.30	.30

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05