Picking a (poor) partner: A relational perspective on acquisitions*

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Abstract: Numerous studies have found that mergers and acquisitions destroy value. What might account for these poor decisions? Using comprehensive data from the advertising industry, we found that the probability of being acquired rose but that the performance of merged entities declined – both losing clients and selling less to the clients retained – with the number of common clients (indirect ties) connecting the target to the acquirer. Two potential mechanisms could account for this pattern of results. Either managers hold (positively) biased beliefs about those connected to them through common clients, or they restrict their searches for potential acquisition partners to those they already know, despite the disadvantages of doing so.

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Mergers and acquisitions significantly shape the evolution of firms and industries.[1] For firms, these events provide a means of growing. Merging with or acquiring an existing entity can allow an organization to gain efficiencies by consolidating operations or to enter a new region or line of business more quickly and with less execution risk. For industries, these events reconfigure the competitive landscape. Within-industry mergers reduce the intensity of competition, and cross-industry combinations can introduce heterogeneity across firms in their interests and capabilities. Strategy and organization scholars have therefore devoted much attention to understanding these events.

One of the most consistent findings has been that mergers and acquisitions hurt organizational performance. Shareholders suffer both short- and long-term erosion in the value of their holdings (Langetieg 1978, Agrawal et al. 1992; for a review, see Agrawal and Jaffe, 2000); firms grow more slowly following acquisitions (Barnett and Sorenson 2002); and, in the end, acquirers often sell off the firms that they bought (Kaplan and Weisbach 1992).

A variety of explanations have been offered for these adverse outcomes. Managers of acquiring firms, for example, may consider their equity overvalued relative to that of other firms (Shleifer and Vishny 2003; Savor and Lu 2009), or they may have personal incentives to grow their firms, even at the expense of profitability (Bliss and Rosen 2001; Grinstein and Hribar 2004). Or, they may underestimate the difficulty of integrating distinct cultures and operational routines (Roll 1986; Hayward and Hambrick 1997; Weber and Camerer 2003; Malmendier and Tate 2008).

Though these theories can all account for the poor average performance of acquisitions, they have little to say about the variation in performance across events. But empirical

[1] We use the terms "merger" and "acquisition" interchangeably. Though the press often uses "merger" to refer to events that combine firms of nearly equal size, from a legal and operational point of view, nearly all inter-organizational combinations involve one firm acquiring ownership of another firm and assuming managerial control of it.

studies have also found that the owners of acquiring firms actually profit from 30% to 40% of acquisitions (e.g., Bradley et al. 1988). What could explain this variation in acquisition outcomes?

We argue that a relational perspective holds considerable promise for explaining this variation. Given the limited extent to which competitors can legally interact, one might believe that relationships should have little influence on within-industry mergers and acquisitions. But that expectation misses the fact that firms weave webs of relationships that extend beyond their own industries. Though they may not interact directly, they do have a variety of indirect relationships – third-party ties – through common clients and shared suppliers and service providers and through hiring one another's past employees. These third-party ties could influence both the choice of acquisition target and post-merger performance.

At first blush, one might expect these third-party connections to improve acquisition performance. To the extent that these relationships provide private information on potential targets (Granovetter 1985; Sorenson and Stuart 2001), for example, acquirers might choose better partners. This intuition, however, assumes both that these third-party relationships provide acquirers with information about the most attractive potential acquisitions and that acquirers evaluate targets with and without common connections with equal objectivity.

Such conditions seem more the exception than the rule. Firms, for example, often share third-party connections only with their closest competitors (Walker et al. 1997; Stuart 1998; Powell et al. 2005). Managers moreover have been found to hold those with connections to them in higher regard (Sorenson and Waguespack 2006). Third-party connections could therefore give rise to suboptimal combinations for a variety of reasons. Some stem from the selection side: Acquirers may overlook potential partners with stronger strategic complementarity. Or, believing that they have sufficient insight into the quality of the acquisition target, they may engage in less intensive due diligence. Others relate to the integration process: Clients, suppliers and other partners that the firms being combined shared prior to their merger – the third-party connections – might receive undue attention, to the detriment of those who had relationships with only the acquirer or the acquired. To test these ideas empirically – that third-party ties influence acquirers' choices of acquisition partners and that this fact has negative implications for performance – we assembled data on the global advertising industry from 1995 to 2003. Our analyses focused on horizontal acquisitions—that is, the combination of two previously-independent advertising firms.

A RELATIONAL PERSPECTIVE ON ACQUISITIONS

An extensive and ever-growing literature has repeatedly demonstrated that relational factors strongly influence the choice of exchange partners. Both individuals and organizations tend to buy from suppliers from whom they have bought before (Kollock 1994; Uzzi 1997; Hoetker 2005). Organizations more commonly form alliances with those with whom they have partnered before or with whom they share third-party ties, a partner of a partner (Larson 1992; Gulati and Gargiulo 1999). Venture capitalists prefer to invest with similar others and in firms located near to them (Sorenson and Stuart 2001, 2008). The list could go on.

Four logics of action have been used to explain these effects. First is a logic of exposure: Actors more similar in their interests or characteristics, or located more physically proximate to one another have a higher probability of interaction. In part, this effect stems from the fact that actors who share a common interest, belong to the same organization or are located near to one another in either social or physical space have a greater chance of being in the same place at the same time and therefore of meeting by chance (Stouffer 1940; Feld 1981). Social structure therefore restricts the range of possible partners. But mere exposure also has a second effect: Familiarity engenders positive affect towards objects and individuals and consequently leads to biased beliefs in their favor (Kollock 1994; Sorenson and Waguespack 2006; Casciaro and Lobo 2008).

Second is a logic of homophily: Even among the set of potential partners met, actors prefer to interact with those similar to them (McPherson et al. 2001). That preference may stem either from the individuals or employees involved receiving a benefit from the interaction itself – they simply enjoy their time together – or from greater similarity assuaging the concerns that might otherwise have arisen about the quality or trustworthiness of their exchange partners (Sorenson and Stuart 2008; DiPrete 2011).

Third is a logic of information access: In many transactions, buyers worry about the quality of their exchange partners or of the products and services that they sell. When they can only assess this quality *ex post* – such as with the tastiness of the food or the attentiveness of the staff at a restaurant – relationships can inform buyers' choices. Prior experience with the vendor provides direct information as to the quality to expect. In its absence, referrals from trusted affiliates can serve as a substitute (Granovetter 1985; Sorenson and Stuart 2001). Buyers therefore have better information about sellers to whom they have direct or indirect connections.

Fourth is a logic of embeddedness: Many exchanges entail vulnerability on the part of one or both parties. One side may be able to act opportunistically by not holding up its end of the agreement. Or, the exchange might involve ongoing investments. Prior relationships and common third-party connections can then instill confidence that partners will not renege on the agreement and that they will invest in joint activities (Raub and Weesie 1990; Uzzi 1997). To the extent that the actors involved anticipate these post-agreement effects, moreover, these expectations could also influence who they choose as an exchange partner.

By and large, however, these logics have not informed our understanding of the selection of acquisition targets or of the performance of mergers and acquisitions.[2] That is not to say that a relational perspective has been completely absent. Research has found, for example, contagion through the members of corporate boards in the propensity to acquire (Westphal et al. 2001), in the prices paid for firms (Haunschild 1994) and in the adoption of defense mechanisms against hostile acquisitions (Davis 1991). But a relational perspective on mergers and acquisitions remains underdeveloped.

Given the vibrancy and extensiveness of research on social structure, it may seem surprising that these logics have not penetrated more deeply into the study of mergers and acquisitions. In part, this inattention likely stems from the fact that the groups of scholars interested in acquisitions and in social structure remain somewhat disjoint. But in large part, it also reflects a data issue: Observing relationships between organizations, particularly those connecting competitors, can prove difficult. These firms rarely have direct connections; antitrust regulation would often prohibit them. Following third-party connections through common relationships to buyers or suppliers – the approach pursued here – meanwhile requires detailed information on these inter-industry exchanges. We nonetheless see ample promise in adopting a relational perspective on mergers and acquisitions.

Selecting acquisition targets

Choosing a firm to acquire is not easy. Potential acquisition targets vary not only in their quality but also in their complementarity with the acquiring firm. Many of the dimensions on which acquiring firms would like to assess potential partners, moreover, remain difficult to evaluate even after deep due diligence: Does the company have strong relationships with

[2]For exceptions, see Porrini (2004) and Zaheer et al. (2010), who examined investors' reactions when firms acquired targets with whom they already had strategic alliances.

its customers? How reliable and robust are its internal systems? Does it have a compatible corporate culture?

Two additional factors further complicate these choices. First, acquiring firms face an information asymmetry (Hansen 1987). Owners and managers of an acquisition target understand its strengths and weaknesses better than the acquirer. But those owners and managers often have their own goals, perhaps wishing to promote poor acquisitions or to discourage profitable ones. As a result, acquiring firms cannot rely on the information they receive from these target firms. Second, a merger initiates a long-term commitment, one not easily reversed. Failure to select the right target therefore can have catastrophic consequences for the firms involved.

Given the uncertainty about the quality of potential partners, the information asymmetry inherent in the situation and the costliness of poor choices, the selection of acquisition targets represents precisely the type of transaction where one would expect choices to depend strongly on inter-organizational relationships. In choosing among targets, at least three of the classes of mechanisms outlined above would predict that acquirers will prefer targets with whom they share third-party ties.

First and foremost, third-party connections increase the odds of contact (exposure). Competing over clients, suppliers and employees leads to an awareness of the other firm, increasing the odds that acquirers consider these firms for acquisition. But third-party ties often also lead to direct interaction as well. Servicing a common client, for example, may require suppliers to coordinate. Or, employees moving from one firm to another may retain personal relationships with individuals at their prior employers.

Common connections therefore might also lead to biased beliefs in favor of these firms. Experimental and field studies suggest that individuals prefer to buy from sellers with whom they have had prior interactions and that they evaluate their goods more highly, particularly in situations where uncertainty surrounds their quality (Kollock 1994; Sorenson and Waguespack 2006). To the extent that acquiring managers have had contact with some acquisition targets through their common connections, they may therefore see them as higher quality and prefer them over those without shared third-party ties.

Second, these indirect relationships allow acquiring firms to access more, and more reliable, information about potential acquisition targets. Common third parties can offer more objective assessments of the strengths and weaknesses of their exchange partners than those actors would provide directly (Sorenson and Stuart 2001; Uzzi and Lancaster 2004). Conversely, potential acquirers might worry about adverse selection when considering the acquisition of those to whom they do not have connections. If the target has so much to offer, why has it not been pursued by others that know better the firm and its employees? The greater availability of information would therefore also lead acquiring firms to prefer targets connected to them through third-party ties.

Finally, following the embeddedness argument, acquiring firms may consider potential partners with third-party ties more trustworthy. Third-party ties facilitate trust in multiple ways. Direct interaction – such as through coordination or social interaction – engenders trust (Blau 1964; Molm et al. 2000). Shared contacts can also relay information – in the form of gossip – about the probable trustworthiness of these common connections (Burt and Knez 1995). The very existence of shared third-party ties moreover helps to ensure trustworthiness. To the extent that the acquiring and acquired firms value these connections, they would not want to jeopardize them by behaving badly (Raub and Weesie 1990; Greif 1993).

Trust matters for a variety of reasons but most notably it can facilitate post-merger integration. Following an acquisition, employees of the acquired firm (as well as of the acquirer) face uncertainty as to how their roles and responsibilities will change, possibly even as to whether they will keep their jobs. They therefore have strong incentives to defend the status quo. But realizing the synergies and cost savings available from combining companies requires integration of their activities and therefore rarely proceeds effectively without employees willing to cooperate, in the process potentially leaving themselves and their jobs vulnerable. Given the importance of trust post-acquisition, the logic of embeddedness would therefore also suggest a tendency to acquire alters with third-party connections.

At least two of these factors – exposure and embeddedness – ought also increase the odds that the target accepts an offer. Favorable opinions of the acquirer due to prior exposure likely increases the perceived attractiveness of an offer to the target. Similarly, trust emerging from embeddedness may help to assuage the fear, among employees of the target, of their fates post-acquisition as well as to instill confidence that integration will proceed smoothly. We therefore expect:

Hypothesis 1. The probability that an acquiring firm acquires a particular target firm increases with the intensity of the third-party ties connecting them.

We nonetheless should note that strategic considerations would suggest a similar relationship. To the extent that third-party ties arise from competition – for customers, for employees or for suppliers – the merger of firms connected through them potentially reduces the intensity of competition. That reduction in competition, in turn, could allow the combined entity to charge its customers more and to pay its employees and suppliers less, thereby increasing its profitability (Stigler 1950).

Although both strategic considerations and relational motives could account for the preference for acquiring targets connected through third parties, they differ in the circumstances under which one would expect this relationship. In particular, the relational mechanisms of exposure and information access should become increasingly important as acquirers consider businesses more distant from their own operations. Acquirers will generally not understand these novel markets and regions as well as they do their own (Capron and Shen 2007; Ragozzino and Reuer 2011). They therefore must rely more heavily on external information – the most trusted of which will come from third-party ties (Sorenson and Stuart 2008; Meuleman et al. 2010) – to evaluate the quality and compatibility of potential acquisition targets. The importance of the information garnered through third-party ties should therefore increase with the distance between the acquirer and target.

As their ability to evaluate these deals declines, acquirers also likely resort to less deliberative means of coming to a decision, such as relying on a (good) gut feeling (positive affect). As noted above, exposure produces positive feelings toward others in both the lab and the field (e.g., Zajonc 1968; Casciaro and Lobo 2008). Psychologists have also found substantial evidence that people use these feelings for gauging whether they have sufficient information and for assessing the extent to which a choice might have negative consequences (Loewenstein et al. 2001; Tiedens and Linton 2001). The logic of exposure therefore also suggests that third-party connections would become increasingly important in influencing choice as potential targets became more distant.

Hypothesis 2. The positive relationship between third-party ties and target selection increases with the distance between the acquiring firm and potential targets.

Post-acquisition performance

With few exceptions, the literature has largely assumed that actors profit from picking partners via social connections. Exchanging with existing partners or partners' partners has been associated with benefits such as discounted pricing and priority in the allocation of resources (Uzzi 1999; Uzzi and Lancaster 2004). Empirical research has also frequently found a positive association between firm performance and structurally embedded exchange (e.g., Uzzi 1997; Rowley et al. 2000; Gulati and Sytch 2007).

One might similarly expect a positive correlation in the case of acquisitions. To the extent that third-party affiliations provide acquiring firms access to information about acquisition targets, they could choose partners with stronger strategic, operational and cultural complementarity and pay more appropriate prices for the assets that they acquire. Because common connections give the acquirer insight into the operations of the target, they may also facilitate integration planning. And, to the extent that acquirers trust these organizations (and vice versa), one would expect post-merger integration to proceed more smoothly.

But this expectation relies on two implicit assumptions: (i) that third-party affiliations connect acquirers either to the most attractive potential targets or to a representative sample of them; and (ii) that these connections do not bias acquirers' beliefs about targets. Acquiring firms could then select the best from those with common connections. The anticipation of a positive relationship between third-party ties and acquisition performance therefore discounts the importance of exposure both in restricting choice and in engendering bias.

Both of these assumptions seem unwarranted. Consider first the issue of bias. Even if acquirers had common connections to all of the most appropriate targets, biased beliefs in favor of those sharing third-party ties could lead to lax due diligence. Feeling more familiar with these companies, acquirers might invest less in assessing their underlying strength and compatibility. Common connections also act as referrals, attesting to the quality of the target, potentially creating a false sense of security. When interpreting the information they gather, moreover, acquirers may view it in an overly favorable light, misinterpreting their positive affect towards the target, due to prior exposure, for a favorable intuition about the firm's promise as a partner (Sorenson and Waguespack 2006). Superficial examination of potential partners prior to acquisition, in turn, raises the risk of acquiring an organization with internal problems or with an incompatible culture or routines, or at too high of a price.

The most promising matches may also not have third-party affiliations with the acquirer. Third-party ties commonly connect quite similar firms—those in the same places, operating in the same segments of the market, competing for customers, and often poaching employees from one another. A reliance on third-party connections to guide the choice of acquisition targets will therefore promote the pairing of highly homogenous partners. But insufficient variety can pose problems. Similarity, for example, reduces the scope for recombination to develop novel products or to extend sales (Capron et al. 1998; Capron and Hulland 1999). It may also foment political entrenchment within the firm and with it an emphasis on the exploitation of existing businesses over the exploration of novel ones. Consistent with these ideas, recent research has found that investors react more positively to acquisitions of firms with complementary, rather than redundant, resources (Kim and Finkelstein 2009), and that firms in high-technology industries produce higher-quality inventions post-merger when they combine organizations with non-overlapping intellectual capital (Makri et al. 2010).

Even if managers understand and appreciate these issues, they may nevertheless find them difficult to avoid. If they only have reliable information about and trust in potential partners connected to them through either direct or indirect ties, the set of available partners may not include those best suited to the acquirer's needs. Common connections can increase the efficiency of the search process, but they necessarily restrict the range of choices considered and therefore potentially produce lower quality matches. We therefore expect that acquisitions guided by these shared relationships will underperform other acquisitions.

Hypothesis 3. Third-party connections between acquiring and acquired firms pre-merger will be associated with lower levels of post-merger performance.

METHOD

Acquisitions in advertising

To investigate how a firm's pre-existing third-party ties influence its choice of acquisition target and the subsequent post-merger performance, we gathered information on the worldwide population of advertising firms, from 1995 to 2003, and on the mergers and acquisitions occurring among those firms during that period. Advertising provides an unusual opportunity for us to test our theory because industry registers have systematically tracked one type of third-party tie, the relationships between advertising firms and their clients.

Advertising firms offer a variety of services, including analyses of clients' positioning and of consumers' perceptions of their products, proposals for advertising solutions, and the creation and implementation of advertising campaigns. Advertising campaigns, in turn, can include print and television advertising, direct marketing, promotional sales, public relations, market research, and event marketing. According to Nielsen (2012), advertising expenditures worldwide totaled to nearly a half-trillion dollars in 2011 and they continue to grow faster than the economy as a whole.

Although advertising has included and continues to include thousands of small, independent agencies, the industry has been consolidating. From 1961 to 2001, the share controlled by the four largest firms rose from 11% to 38% (von Nordenflycht 2011), and this concentration has continued to rise over the last decade. The forces behind this consolidation have been a subject of debate. Though larger firms can negotiate better prices when buying advertising time and space, the returns to scale in media buying remain small relative to perceived quality differences across firms. One plausible force for consolidation has been the changing client landscape: Clients have become larger and more global and many claim to prefer agencies capable of coordinating and executing national, and even international, advertising campaigns (von Nordenflycht 2011).

As a setting, acquisitions in the advertising industry fits well with the factors thought to foster relationship-based exchange. Advertising firms produce highly differentiated services. Their assets are their people, their reputations and their client relationships. And they are generally privately held. These factors combine to create a daunting problem for acquirers: They must assess the quality of potential partners and their assets with limited publicly-available and verifiable information, aware that the managers of potential targets have a better understanding of the value of these firms than they do. By transmitting private information and facilitating trust across organizations, inter-organizational relationships serve as the lubricant of exchange necessary to expedite these sales.

Acquisitions in this industry also have another useful feature: Hostile takeovers almost never occur. Because all but the largest advertising firms have been organized as partnerships, the owner-managers of these firms have full veto power over any potential acquisition. We therefore need not worry about factors that might influence the ability of a target to fend off unwanted suitors.

Data

We assembled our dataset from a variety of sources. The *Standard Directory of Advertising Agencies* – also known as *The Redbooks* – published by Lexis Nexis provided information on all advertising firms. Our data on mergers and acquisitions came from SDC Platinum, an online database maintained by Thomson Reuters, and the attributes of the client firms came from annual data discs of the Corporate Affiliations database, also published by Lexis Nexis.

The Redbooks, published annually, represent the most comprehensive source of information on advertising agencies. Each record includes the advertising firm's location, size, annual billings and executives' names and titles. Most important for our purposes, these entries also report the names of the clients that each agency serves, allowing us to identify common clients (third-party ties). These directories do not, however, provide any information about these clients beyond their names nor do they even use a consistent set of names.

Client names vary in their spelling, completeness and division of the client firm. For example, one agency might report its client as Ford and another as Ford Motor Company or as Ford–Japan or as Mercury. To determine whether these client names referred to the same underlying firm – as well as to include client-level characteristics – we matched clients to Corporate Affiliations, which includes data on public and private companies worldwide with annual revenues of more than $10 million. Importantly, the database includes information on corporate hierarchies and has entries for both parent firms and their subsidiaries, allowing us to match client accounts held at a subsidiary level to their corporate parents.

Because our database included more than 1.3 million client names from *The Redbooks* and over 1.8 million entries from Corporate Affiliations, matching by hand proved infeasible. We therefore developed an algorithm to assign client names to entries in Corporate Affiliations. Our algorithm first parsed the client names into individual words (up to a maximum of five). It first assigned names to entries that matched on all words (regardless of their order). For cases where no complete match existed, the algorithm determined the rarity of each word in the Corporate Affiliations data and weighted the possible matches for each client according to the inverse rarity of the words in common. Each word contributed from zero to one to the overall score, which ranged from one to five. For example, "Arcteryx" appears only once in Corporate Affiliations, so a match on that word would receive a score of one ($= 1/1$); "America" meanwhile belongs to several thousand names, so a match on that would receive a score of almost zero ($= 1/64,098$). The algorithm would therefore weight the client "Arcteryx America" as a several thousand times better match to Arcteryx than to the numerous other companies and subsidiaries with America in their name. We then assigned client names to entries in Corporate Affiliations based on the best match, assuming that the algorithm found at least one "good" match.[3]

Our algorithm succeeded in assigning unique identifiers in Corporate Affiliations to 55% of the client names. Most of the unmatched names come from organizations not found in Corporate Affiliations, such as small firms, non-profits and political campaigns. Analyses of random samples revealed that our algorithm produced a false positive rate – assigning the client name to the wrong identifier – of less than 1% and a false negative rate – not assigning a match where one existed – of no more than 5%. In total, our data set includes information on 9,623 advertising agencies serving 21,934 unique and identifiable (ultimate parent-level) clients from 1995 to 2003.

Our arguments about the effect of common clients on target choice apply to horizontal mergers between advertising firms with no prior ownership ties. A research assistant exam-

[3]Through manual examination, we determined that a good match – one with a low probability of producing a false positive – required matching on at least one word that appeared fewer than 14 times in Corporate Affiliations or on at least two words that each appeared fewer than 30 times.

ined acquisitions listed in SDC Platinum between 1995 and 2003 to eliminate events that involved (i) the acquisition of an advertising agency by a non-advertising firm, (ii) the acquisition of a non-advertising firm by an advertising agency, (iii) acquisitions in which one firm had prior ownership in the other, and (iv) the transfer of a subsidiary from one advertising agency to another.[4] In total, we identified 67 acquisitions between 1995 and 2003 meeting these criteria. The need for information on these firms and the identities of their clients both pre- and post-acquisition nevertheless reduced the final sample to 37 events.[5]

Having a limited number of focal acquisitions made it feasible to investigate each one. By reading articles written at the time, we gained some insight into the ostensible motivations behind these acquisitions. Acquirers reported a somewhat heterogeneous set of interests: Acquisition of the target's client accounts represented the single most commonly cited reason for the acquisition (11 cases). Other reasons mentioned included: (i) to expand the scope of the firm, usually in terms of geography (6 cases), (ii) to consolidate operations in some particular industry segments (5 cases), and (iii) to acquire talent from the acquisition target (3 cases). These rationales, however, appeared uncorrelated to the existence of common clients. Targets almost uniformly stated that their interest in being acquired stemmed from the possibility of gaining access to the resources of the acquirer.

Partner selection analyses

In the first set of analyses, we estimated the effect of common clients on the choice of target acquired. Ideally, one would have information on all of the targets considered both explicitly

[4]SDC Platinum only includes transactions with a value of at least $1 million.

[5]Comparisons of this final sample to all 67 acquisitions revealed the acquired firms in the sample to be smaller in terms of annual billings and employees. This fact should mitigate against many of the common drivers of poor acquisition performance. With smaller, private firms, acquirers generally need not worry about competing against other buyers nor about the relative valuations of their public equity (e.g., Shleifer and Vishny 2003; Capron and Shen 2007).

and implicitly by acquirers. But no such data exist. Managers of acquiring firms may not even understand their own consideration sets, to the extent that some selection occurs at a subconscious level. To address this issue, we adopted a case-control design, with an intended case-to-control ratio of 1:10.[6] Our case sample included the acquirer-target pairs involved in the actual mergers. We then used coarsened exact matching (CEM) to construct our control sample, pairing each acquiring firm with observationally-equivalent targets that they could have acquired but did not.[7]

Selecting observationally-equivalent controls involves a tradeoff: Coarser matching reduces the value of the matching in adjusting for differences across the case and control groups but increases the number of available matches. Finer-grained matching, on the other hand, limits the number of equivalent matches – potentially to zero – but better accounts for variation in the data. Matching at either too coarse or too fine-grained a level will therefore reduce the efficiency of the estimates. The results reported below use controls drawn at random (without replacement) from the population of potential targets in the same geographic region (continent), in the same annual billings quartile, and in the same client size quartile (defined by the count of client accounts held by the firm) as each case.[8] Because we constrained the selection of controls to matching exactly on multiple dimensions, several cases had fewer than ten eligible controls. The final sample for the first set of analyses therefore included 324 observations: 37 cases and 287 controls.

Because acquirers essentially drive the selection of partners, with targets playing a more

[6]No hard rule governs the choice of a ratio, but with fewer controls per case produce larger standard errors. Our results remain significant down to a ratio of 1:2.

[7]Recent research suggests that CEM has several advantages over other techniques that match on observables, such as propensity score matching (for a review, see Iacus et al. 2012).

[8]Additional analyses revealed that the results remained robust to courser matching, even to the extent of treating the entire population as equivalent, and to more fine-grained matching, in particular to matching geographic region at the country level. Both courser- and finer-grained matching nevertheless produced larger standard errors.

passive role – saying yes or no to a particular offer – we modeled the process as a conditional logit regression (also known as the McFadden choice model). We set a binary dependent variable, acquisition, to one for the actual mergers (the cases) and to zero for the unrealized combinations (the controls). We conditioned our models on the set of matched cases and controls, thereby controling for the characteristics of the acquiring firm and for the variables on which the cases and controls have been matched.

Acquisition performance analyses

In the second set of analyses, we examined the effect of acquisition on the performance of the acquired firms. Studies of post-merger performance typically have relied on either cumulative abnormal returns (CAR) or return on assets (ROA) as performance measures (Haleblian et al. 2009). Neither of these measures, however, offers an attractive assessment of performance here. CAR exists only for publicly-traded firms. Given that public ownership remains rare in advertising except for multiagency, multinational holding companies, using this performance metric would limit our sample to mergers of these public firms. ROA, meanwhile, poses a problem because advertising agencies have little in the way of assets. With small denominators, these ratios become difficult to compare both across firms and within-firms over time. Agencies therefore rarely report ROA. We instead focused our analysis on two types of operational measures of performance: client retention and billings per client.

Client retention. Given that agencies typically have few major clients, their retention matters greatly to firm performance (Baker et al. 1998). We therefore created two measures of relationship termination to count the cumulative number of client relationships that dissolved following the merger. One can measure these dissolutions at either the account level or the relationship level because any given client may have multiple accounts with an advertising firm. We therefore constructed two versions of this measure for each post-merger year: the cumulative count of client accounts terminated and the cumulative count of client relationships terminated. Whereas in the first case, a client could drop some accounts but not others with the advertising firm, in the second instance, the client closes all of its accounts with the firm.

To construct these measures, we tracked client accounts for three years prior to the merger and three years after it. We coded an account as dissolved in the first year the advertising firm no longer listed the client in its *Redbooks* record. If we observed a discontinuation of all of the accounts with the client, we also considered the relationship dissolved. For both measures, we then summed these events into cumulative annual counts of relationships lost. Post-merger, these measures therefore count the cumulative dissolutions of the accounts and relationships held by the target firm at the time of the merger (for both cases and controls). The sample for the client account loss analysis included 1,169 firm-years.

To estimate the effects of common clients pre-merger on post-merger performance, we adopted a differences-in-differences-in-differences (triple differences) approach. The basic differences-in-differences (diff-in-diff) set up compares the changes in a set of actors exposed to a treatment to those not exposed to it. In our setting, treatment means being acquired. We compare the trajectories of our cases (those acquired) to our controls (similar firms that remained independent). The diff-in-diff estimator essentially subtracts the average change in the control group from the average change in the treatment group, thereby removing confounds that could result either from trends or from stable differences across the groups receiving and not receiving the treatment (Ashenfelter and Card 1985). When the treatment has been randomly assigned, one can interpret the estimated effects as causal (as opposed to simply correlational).

But it seems improbable that acquisitions would occur at random, as required by the diff-in-diff estimator. We therefore introduced an additional differencing into the estimator to purge our results of factors correlated with being acquired, a triple differences approach (e.g., Gruber 1994; Butler and Cornaggia 2011). Our theory moreover pertains to the differential effects of acquisition as a function of third-party ties. One can think of this method as first estimating differences-in-differences for firms with a particular number of common clients: In other words, (i) how do merged firms with one or more common clients pre-merger change after the merger relative to firms with the same number of common clients that remained independent, and (ii) how do merged firms with no common clients pre-merger change after the merger relative to firms without common clients that remained independent. Each of these differences provides an estimate of the effect of merging, conditional on some number of common clients. The triple differences estimator then differences between these differences – (i) and (ii) – to arrive at an estimate of how the effect of merging depends on the number of common clients. Our estimates therefore net out selection in who gets acquired and focus on variation in the effects of acquisition as a function of common clients.

Because the dependent variable in the dissolutions analysis represents a count, we estimated these models using maximum likelihood fixed effects Poisson regression, with fixed effects for the case-control groups. To adjust for differences in the number of clients across firms, we included the number of relationships as an exposure term (Cameron and Trivedi 1998). The analysis therefore effectively estimates the rate of client loss.

Billings per client. But client loss measures miss the fact that firms might intentionally focus on a smaller set of clients, potentially retaining only the more profitable ones. We therefore created a measure, billings per client, to capture the average profitability of each relationship. Billings actually refer to the cost of the ads placed by clients. But because advertising firms charge a 15% commission on these billings, with little firm-to-firm variation (Baker et al. 1998), any change in billings implies a proportional change in revenue accruing to the agency.

Using this measure required two modifications to the research design. First, because merged firms usually report billings at the firm level, we could not focus only on the acquired targets, as in the client retention analysis. Instead, we analyzed the combined entities (both pre- and post-merger). Second, once we moved to treating the merged firms as a unit, our existing control cases no longer proved sufficient because they only accounted for the target side of the merger.

To generate an appropriate comparison set, we constructed a sample that matched the merged agencies (cases) with a set of synthetic counterfactual mergers (controls)—combinations of firms that could have occurred but that did not. We began by creating two separate matched samples, one for the acquirers, the other for the targets. For the targets, we used the same set as for the other models. For the acquirers, we followed the same CEM procedure, choosing firms at random without replacement that matched the acquirer on geographic region, billings quartile and client size quartile. We then randomly combined these matched potential acquirers with the matched potential targets to create synthetic mergers. The billings analysis included 1,097 firm-years.

We constructed our dependent variable in the following manner: For merged firms post-merger, we simply divided the (logged) total billings reported by the acquirer by the (logged) total number of clients listed across all of its subunits.[9] Pre-merger, we summed the billings

[9]In some cases, *The Redbooks* appeared to carry forward billings information from one year to the next. If true, this practice should generate more conservative estimates of the effects (because changes would not appear in the data). We also estimated the performance models excluding observations from firms that reported no change in their annual billings or client accounts, obtaining substantively equivalent results.

of the acquiring firm and the acquired firm, logged them, and divided them by the (logged) summed counts of clients listed by the two firms. We similarly constructed this measure for the controls by summing the billings of both firms, logging the sum, and dividing it by their (logged) combined client counts. Logging the numerator and denominator accounted for the fact that larger agencies tend to serve larger clients. Hence, the analyses essentially estimate whether client account size scales at a different rate, relative to firm size, depending on the existence of pre-merger third-party ties.

Our identification approach again relied on triple differencing. Hence, we essentially examined whether the firms that merged managed to grow their billings-per-client faster than those that did not and the extent to which that differential depended on whether the firms involved shared clients prior to the merger. As in the client retention analysis, our models included fixed effects for each case-control group. Our table also reports standard errors clustered on these groupings (Bertrand et al. 2004). To address serial correlation in the data, we estimated this outcome in terms of differences, including the lagged dependent variable as a covariate in a linear regression. To control for all annual time-varying factors shared across observations, we included indicator variables for each year relative to the time of the merger.

Independent variables

Common clients. Our measure of third-party ties counts the number of clients shared by the acquiring firm and each potential target. Depending on the particular mechanism at play, one might construct this variable in different ways. For example, if acquirer trust in the client mattered most, then one might weight each tie according to the tenure of the acquirer-client relationship. Or, if one thought that common clients primarily provided a setting for potential interaction, then weighting by the time that the two agencies shared the client might more accurately capture the effect. All of these versions of this measure produced equivalent patterns of results. We report the models using the simple logged count because it produced the best-fitting estimates.

For the partner selection models, we measured proximity of the acquirer to potential targets on two dimensions: industry focus and geographic location. Prior research indicates that the information asymmetry between the acquirer and the target and the difficulty of evaluating a target increase with industry distance (Capron and Shen 2007). We therefore created a measure of shared industries by assigning all clients to four-digit SIC codes and counting the number of codes in which both the acquirer and the potential target had clients. Prior research has also found that information asymmetry increases with the geographic distance between the acquirer and the acquired firm (Ragozzino and Reuer 2011). To create this variable, we first assigned agencies to locations on the basis of their headquarters and then used spherical geometry to compute the geographic distance in terms of the (logged) distance in miles between the acquiring firm and each potential target, along the lines of Sorenson and Stuart (2001). To test Hypothesis 2, we interacted the logged count of common clients with the number of shared industries and with the geographic distance between each pair of firms, centering the variables prior to multiplying them.

In the partner selection models, the acquiring firm remains constant in each case-control set. The design therefore controls for all characteristics of the acquiring firm. Meanwhile, the matching of the acquired firm to the controls on region, size and the number of client relationships means that all of these factors have effectively been held constant. We nonetheless adjust for a number of factors that have been found to influence target choice. Rhodes-Kropf and Robinson (2008), for example, found that firm efficiency attracts acquirers. We therefore entered the target firms' annual billings per employee ratio as a control variable. The year founded of the target firm controls for the relative attractiveness of more or less mature targets. To account for variation in client bargaining power (e.g., Chatterjee 1986), we also included Herfindahl indices of the industry concentration of the target firm's client relationships and of the client concentration of the target's relationships. Finally, the count of accounts/relationships controls for any residual variation in the number of clients not eliminated in the matching on client count quartiles.

Table 1 provides descriptive statistics for the partner selection models, reported separately for the cases and the controls. The table suggests that the matching has effectively selected similar controls to the cases. The two samples differed significantly on only three variables: Cases had more common clients and, in large part because of those shared clients, served more common industries. They also had headquarters closer to acquiring firms. On other dimensions, however, cases and controls did not significantly differ.

Following the usual diff-in-diff approach, the models assessing performance included three variables: an indicator set to one if the pair of firms merged, an indicator set to one for the post-merger years, and an interaction of these two terms. To account for the third differencing, we also included the (logged) count of common clients between the acquiring firm and each target pre-merger, as well as the interactions of this variable with the other diff-in-diff terms. Table 2 provides the descriptive statistics for the performance models, with the upper panel detailing the sample of acquisition targets and matched controls used for estimating client retention while the lower panel describes the sample matched on both the acquirer and the acquired firm used for estimating billings per client.

RESULTS

Partner selection

Table 3 reports our conditional logit estimates of partner choice. All of our tables detail significance levels using one-sided t-tests of the hypothesized effects and two-sided tests for the other coefficients. Model 1 provides a baseline. Only one control has a substantial effect on partner choice: Acquiring firms preferred geographically proximate targets, consistent with past research (Baum et al. 2000). The fact that other factors found important in previous research do not predict selection here provides additional evidence that our matching has been effective in creating comparable sets of cases and controls, similar even on variables not explicitly used to match them.

As anticipated by Hypothesis 1, the count of common clients significantly and positively predicted target choice (Model 2). The effect is large; the difference in the probability of being chosen for a potential target with no common clients versus for one with one common client is as great as the difference for a target located in the same metropolitan area versus one more than 500 miles away. Model 3 introduces interactions between the count of common clients and our distance measures to test Hypothesis 2.[10] Both interactions had the expected effect: Common clients had a positive interaction with geographic distance, meaning that the probability of choosing a partner with common clients increased with physical distance. Common clients and shared industries meanwhile had a negative interaction, implying that the odds of choosing a partner with common clients also increased among potential targets serving distant industries.

Though our results appear to reject the null of no effects, spatial autocorrelation may

[10]Though one might worry that the non-linearity in these models could complicate the interpretaton of the interaction terms (e.g., Hoetker 2007), linear probability models produced the same pattern of results.

nonetheless lead to inefficient standard errors (Dekker et al. 2007). To determine whether such autocorrelation might influence our conclusions, we estimated our models using two permutation-based approaches: Freedman-Lane Semi-Partialing and Double Semi-Partialling. Both of these methods appear to generate efficient standard errors robust to spatial autocorrelation emerging from a variety of processes (Dekker et al. 2007). However, since the reliability of these methods has not been established for non-linear models, we specified these robustness checks as linear probability models, with fixed effects for case-control groups. These analyses yielded qualitatively-equivalent results but with much smaller standard errors and much larger t-tests than those estimated by the conditional logit. If anything, the conditional logit therefore appears to generate overly conservative estimates of the effects.

As noted above, however, one could interpret this pattern of effects as consistent with multiple relational mechanisms. Exposure, information access and embeddedness would all lead one to expect mergers and acquisitions to occur more regularly among organizations with common third-party connections. The results on performance nevertheless allow us to adjudicate between these various accounts. Two of the mechanisms – information access and embeddedness – predict a positive relationship between common clients pre-merger and post-merger performance. By contrast, the restricted availability of potential partners and biased perceptions of alters as a result of common clients – both stemming from the logic of exposure – point to a negative relationship between these third-party ties and performance.

Acquisition performance

Figure 1 depicts the raw (unadjusted) survival rates of client relationships post-merger. The solid line represents acquired firms with no common clients pre-merger while the dashed line denotes those with at least one common client. On average, acquired targets with pre-merger third-party connections lost clients more rapidly than those without them. This bivariate relationship, however, does not adjust for potential confounds. We therefore turn to our multivariate triple differences analysis.

Table 4 reports this analysis, with the first two columns providing estimates of client relationship dissolutions at the account level and the second two providing them at the relationship level. Recall that these models have been estimated as Poisson regressions with the number of client accounts/relationships controlled through an exposure term. One should therefore interpret the estimates as rates of dissolution.

We began by following the usual diff-in-diff strategy, including three variables in the models: an indicator set to one if the pair of firms merged, an indicator set to one for the post-merger period, and the interaction of these two terms. Model 4 indicates that, on average, acquisitions accelerated account loss. Model 6 suggests that mergers, on average, also increased the loss of clients overall, but there the estimates do not allow us to reject the null of no effect.

To account for the potential effects of pre-merger third-party ties (the third differencing), Models 5 and 7 include the (logged) count of common clients between the acquiring firm and each target pre-merger, as well as the interactions of this variable with the other diff-in-diff terms. Our primary variable of interest is the three-way interaction between the count of common clients, the merger treatment and the post-merger period. Consistent with Hypothesis 3, this variable has significant and positive effects in both models, indicating that target firms that shared clients with the acquiring firm pre-merger lost a larger proportion of clients post-merger than those that did not share clients pre-merger with the acquiring firm (relative to potential targets not acquired).

To provide a more intuitive sense of how to interpret the triple differences estimator and the predicted effects, Table 5 reports the implied multiplier rates for all of the cells of the diff-in-diff at the first three levels of common clients (0, 1 and 2). Dissolution rates for the matched control cases with no common clients, during the pre-merger period, serve as the baseline. The top panel reports the calculations for potential targets with no common clients. The first row of that panel indicates that dissolutions among the control cases rose from a multiplier of 1 pre-merger to a multiplier of 1.54 post-merger, an increase of 54% (or a multiplier of 1.54). The second row meanwhile reports that the dissolution rate for acquired firms increased from a multiplier of 1.26 to one of 2.14, a rise of 70%. Among firms with no common clients with their acquirers, then, acquired targets experienced a 10% larger increase in their client attrition post-merger relative to those not acquired.

The middle panel details these calculations for potential targets with one common client with their acquirer. The matched controls here experienced a 25% increase in their client dissolution rate pre- to post-merger. Over this same period, however, the acquired firms went from a multiplier of 1.25 to one of 2.25, an increase of 80%. Hence, acquired firms with one common client experienced a 44% larger rise in their client loss rate relative to their matched controls, a larger performance penalty than that experienced by acquired firms with no common clients. The bottom panel meanwhile demonstrates that this penalty continues to rise with further increases in the number of common clients.

We should note that these results almost certainly underestimate the effects of third-party ties for two reasons. First, our measure of common clients has a higher rate of false negatives than of false positives. Second and more significantly, our measure only evaluates third-party connections in terms of shared major clients. Firms may also share common minor clients, have relationships through board members, through the exchange of employees or through common memberships in organizations outside the industry. Both of these factors imply that many agencies that appear to have no common clients do indeed have third-party ties and therefore differ less than our measure would imply, leading to attenuation bias.

We would also note that the "control" variables in the triple differences estimator point to a number of interesting effects. The indicator variable for being treated, the merged variable, essentially captures selection in who gets acquired. The positive and (marginally) significant coefficient indicates that acquired firms have higher levels of client loss, even pre-merger, than those not acquired. We therefore appear to see adverse selection, on average, in target selection. But the interaction between this variable and the count of common clients has a negative and significant effect. In other words, the existence of common clients reduced the strength of adverse selection in choosing a partner, consistent with the idea that these indirect ties provide access to information about the target.

Given that gaining clients had often been claimed as the primary reason for acquiring the target, our estimates suggest that acquisitions of targets with common clients have been unsuccessful. One might nonetheless worry that the acquired targets have been replacing their clients, perhaps because they found more prestigious or more profitable ones. Model 8 addresses this possibility by estimating the correlates of client additions (the count of accounts added). This model follows the same empirical set up as the estimates of relationship termination with one exception: The models include a (logged) count of the number of accounts that the target had in the prior year to control for differences in scale. Acquired agencies did not differ from non-acquired potential targets in the rate at which they added client accounts nor did acquired targets with third-party ties to their acquirers differ from those without them in this rate. The differences in client attrition rates therefore do not appear to reflect replacement.

One might also worry that our analysis fails to address the fact that acquirers could continue to serve clients from agencies other than the acquired one. To address this issue, we examined whether client relationships migrated from the acquired firms to their acquirers. Table 6 provides a transition matrix for the relationships of the firms involved. For example, the first row indicates that, of the 369 clients served exclusively by the 37 acquired firms in our sample, only 4.6% (17) moved to being served only by the acquiring agency two years after the acquisition.[11] Tabulations for the destination states one year and three years after the acquisition revealed similar transition rates. Thus, though a handful of clients did shift from the acquired targets to their acquirers, these relationships accounted for but a small fraction of the differences in accounts lost and therefore could not explain our results.

Consider also the final column in Table 6. Clients served only by the acquired firm have a far higher rate of leaving than those served only by the acquirer. But, notably, shared clients also have a higher rate of abandonment than those served by the acquirer alone. That suggests that client loss does not stem from acquired firms shifting their focus to shared clients. It also suggests that if acquirers had been motivated to acquire a target to consolidate their control over a particular account – in other words, to reduce account-level competition – that they largely failed to do so (for further exploration of this issue, see Rogan and Greve forthcoming).

Although the client dissolution results suggest that partner selection based on common clients leads to poor acquisition performance, perhaps mergers allow firms to benefit by reducing competition or by culling their client bases to focus on the most profitable ones. Table 7 therefore reports estimates of the effect of mergers on billings per client of the combined firms. A similar pattern of results emerges. Merged entities that combined two

[11] Some of these transitions probably occurred by chance rather than via the intentional shifting of clients across subunits of the firm. Lost clients must go somewhere; they may end up affiliated with the acquirer because it won out over other agencies bidding for the account.

firms that shared clients pre-merger experienced a drop in billings per client post-merger compared to those where the firms involved did not share clients (Model 10). Across all measures of merger performance, we therefore observe effects consistent with Hypothesis 3.

A final concern would argue that mergers may have the goal of controlling costs rather than of expanding revenues. Though the advertising industry offers limited economies of scale, we nonetheless explored this possibility empirically. Using the same sample and set up as for our analysis of billings per client, we estimated the correlates of billings per employee—a measure of the efficiency of the merged entity. We found no significant effects of mergers on the billings per employee ratio of the firms being combined, either on average or differentially across firms depending on their pre-merger common clients. Cost savings therefore do not appear to provide an alternative interpretation of our performance results.

DISCUSSION

We proposed that a relational perspective could help to explain variation in the performance of mergers and acquisitions. We found strong support for this proposition in the advertising industry. Advertising firms tended to acquire agencies with whom they shared common clients (third-party ties). These acquisitions, however, resulted in the loss of clients and of revenue from the clients that they retained. The tendency for acquirers to choose targets with whom they shared third-party ties could stem from a variety of factors. Exposure to the employees of target firms might lead acquirers to perceive them as being of higher quality or as more congenial (Sorenson and Waguespack 2006). Common connections might lead them to prefer these firms because the better access to information that these connections afford helps to mitigate information asymmetry (Uzzi and Lancaster 2004). Or, embeddedness might engender trust and therefore ease post-merger integration (Briscoe and Tsai 2011).

But only one of these mechanisms can also explain the negative consequences of these mergers for the performance of the combined entities. Both increased access to information and trust point to a positive association between common clients and post-merger performance. By contrast, to the extent that exposure introduces a positive bias into acquirers' perceptions of potential partners or restricts the set of targets considered to those less complementary to the acquirer, it will lead to poor interorganizational combinations.

While our focus has been on the advertising agencies, one might wonder how clients experience the merger and what leads them to abandon acquired agencies. Two issues appear central. First, clients suffer from a deterioration – or at least a perceived deterioration – in service. In interviews, clients of acquired agencies frequently mentioned feeling neglected. Second, acquisitions often increase the competitive overlap across clients. Rogan (2014), who studied this issue in detail, noted that clients tried to avoid such overlaps because they saw them as conflicts of interest on the part of the advertising agency.

Though the advertising industry provided an excellent setting for this research, we would expect similar dynamics to occur in other settings and across other types of third-party ties. Kogut and Walker (2001), for example, found results consistent with this idea across the entire economy of Germany. They examined common connections formed through ownership and found that acquiring and acquired firms had more shared paths and far shorter paths connecting them than random pairs of firms from the economy, suggesting that common ownership broadly influences acquirers' choices of acquisition partners. Kogut and Walker (2001) did not, however, examine the performance of these mergers so the performance consequences of these combinations remains an open question.

Our results contribute to research on mergers and acquisitions by bringing a relational perspective to this literature. Existing research has given limited attention to the choice of acquisition target and how this choice influences the performance of the acquisition. The literature therefore has multiple explanations for the poor average performance of mergers and acquisitions but few for the variation in performance. Our results reveal, however, that post-merger performance varies greatly depending on the pre-merger prevalence of third-party ties connecting the acquirer to the target.

Because acquiring firms, on average, acquire those with indirect ties, our findings also suggest a novel explanation for the poor average performance of mergers: the systematic selection of poor partners. In contrast to the negative effects for mergers of firms with common clients, our results pointed to no – or even a positive – effect of mergers on post-merger performance for firms without common clients. Mergers only destroyed value, on average, because they usually combined firms with third-party connections. Our results therefore strongly implicate relationship-based exchange – picking the wrong partners – as one of the primary factors underlying the poor average performance of acquisitions.

How can this behavior exist in equilibrium? Why do managers not recognize the folly of choosing partners with third-party ties? On the one hand, one might consider the rarity of mergers as evidence that managers do (usually) act wisely. But the rarity of these events also means that managers have limited opportunities to update their beliefs. Few firms engage in multiple acquisitions, even over the course of a decade; even fewer acquire both connected and unconnected targets. Managers may also not realize the degree to which relationships influence their choices and therefore not code their decisions as having been influenced by them. Learning in these environments therefore proves vexingly difficult.

Our results also contribute to an emerging theme in economic sociology on the potential pitfalls of doing business with familiar others. At the level of the individual, for example, Casciaro and Lobo (2008) found that people would turn to colleagues they liked rather than their most competent peers for advice and for help. Kollock (1994) and Sorenson and Waguespack (2006) similarly found that prior exchange could lead to positively biased beliefs about the quality of prior partners and therefore to repeated exchange. At the organizational level, meanwhile, evidence has been accumulating that relationship-based exchange can lead to one party exploiting the other (Gulati et al. 2009; Lee 2013). We extend this theme by demonstrating that the downsides of embedded exchange go beyond the dyad. Whereas prior research has focused on friends, acquaintances and prior exchange partners – in other words, direct ties – our results reveal that these effects also appear through indirect ties.

More broadly, one might think of these related streams of research as establishing evidence for a "familiarity trap" in interpersonal and interorganizational networks. March (1991) noted that learning could lead firms to focus too much on the exploitation of their existing resources and competencies at the expense of the exploration and development of new ones, a problem that he labelled the competency trap in organizational learning. Actors face a similar tradeoff with respect to their relationships: They have better information about and rapport with prior partners and partners of partners, leading to the exchange with familiar alters being the easier choice. But restricting their search to this set also prevents actors from exploring whether strangers might offer more compatible matches.

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Table 1: Summary statistics: Partner selection

	Cases		Controls	
	Mean	SD	Mean	SD
Common clients	0.73	0.88	0.33	0.63
Shared industries	3.00	5.17	2.08	4.29
Geographic distance	4.89	3.23	5.82	2.24
Billings per employee	1.93	3.26	1.86	8.20
Year founded	1975.4	23.2	1978.2	15.3
Industry concentration	0.26	0.27	0.28	0.24
Client concentration	0.22	0.24	0.22	0.24
Count of clients	13.86	26.85	8.5	12.64
N	37		287	

Table 2: Summary statistics: Performance

	Cases		Controls	
	Mean	SD	Mean	SD
Accounts terminated	3.69	4.70	2.11	4.56
Relationships terminated	2.93	3.46	1.76	3.78
Accounts added	4.11	5.10	2.74	6.69
Count of accounts	11.33	10.26	8.90	13.93
Count of relationships	9.97	8.15	7.65	10.48
Merger	1	0	0	0
Post-merger	0.36	0.48	0.33	0.47
Common clients	0.73	0.71	0.32	0.60
N	107		1,062	
Billings per client	4.75	1.13	6.48	2.06
Merger	1	0	0	0
Post-merger	0.57	0.50	0.75	0.44
Common clients	0.87	0.79	0.15	0.43
N	133		964	

Table 3: Conditional logit estimates of target firm choice

	Model 1	Model 2	Model 3
Geographic distance	-0.238**	-0.220*	-0.304**
	(0.087)	(0.092)	(0.103)
Shared industries	-0.146	-0.173+	0.098
	(0.096)	(0.096)	(0.132)
Billings per employee	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Year founded	-0.001	-0.001	-0.008
	(0.010)	(0.011)	(0.012)
Industry concentration	1.545	0.805	1.396
	(1.845)	(2.028)	(1.891)
Client concentration	-1.774	-0.616	-0.434
	(2.052)	(2.212)	(2.101)
Count of clients	0.041+	0.013	0.021
	(0.024)	(0.025)	(0.033)
Common clients		1.321*	1.727**
		(0.536)	(0.571)
Common clients			0.234*
$\times$ geographic distance			(0.116)
Common clients			-0.106*
$\times$ shared industries			(0.050)
Observations	324	324	324
Case-control groups	37	37	37
Log Likelihood	-70.08	-66.63	-62.17

Clustered standard errors in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4: Fixed effects Poisson estimates of target firm client terminations and additions

	Terminations				Additions
	Account		Relationship		Account
	Model 4	Model 5	Model 6	Model 7	Model 8
Count of accounts ($t-1$)					.375***
					(0.061)
Merged	0.064	0.230	0.089	0.287*	0.254
	(0.079)	(0.126)	(0.084)	(0.131)	(0.185)
Post-merger	0.220***	0.434***	0.214**	0.403***	-0.126
	(0.064)	(0.073)	(0.070)	(0.079)	(0.251)
Merged × post-merger	0.387***	0.099	0.200	-0.068	0.199
	(0.116)	(0.173)	(0.130)	(0.187)	(0.466)
Common clients		0.234***		0.207***	0.113
		(0.036)		(0.039)	(0.084)
Common clients × merged		-0.243*		-0.276*	-0.066
		(0.109)		(0.118)	(0.180)
Common clients × post-merger		-0.305***		-0.300***	-0.527
		(0.050)		(0.059)	(0.643)
Common clients × merged × post-merger		0.381**		0.387*	0.433
		(0.154)		(0.178)	(0.823)
Year fixed effects	YES	YES	YES	YES	YES
Case-control group fixed effects	YES	YES	YES	YES	YES
Observations	1169	1169	1169	1169	849
Log Likelihood	-2260.8	-2232.1	-2007.8	-1987.5	-810.6

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

Table 5: Estimated multiplier rates of account terminations

Common clients = 0

	$Post = 0$	$Post = 1$	Δ
$Merge = 0$	1	1.54	1.54
$Merge = 1$	1.26	2.14	1.70
diff-in-diff			1.10

Common clients = 1

	$Post = 0$	$Post = 1$	Δ
$Merge = 0$	1.18	1.47	1.25
$Merge = 1$	1.25	2.25	1.80
diff-in-diff			1.44

Common clients = 2

	$Post = 0$	$Post = 1$	Δ
$Merge = 0$	1.29	1.43	1.11
$Merge = 1$	1.25	2.31	1.85
diff-in-diff			1.67

Table 6: Client relationship transition matrix

	Merger (t)	Destination ($t+2$)			
	N	Target	Acquirer	Shared	Lost
Target client	369	25.7%	4.6%	3.5%	66.2%
Acquirer client	26,973	0.1%	77.8%	0.3%	22.7%
Shared client	211	1.9%	24.6%	27.0%	46.5%

Table 7: Fixed effects estimates of changes in billings per client

	Model 9	Model 10
Billings per client ($t-1$)	0.877***	0.864***
	(0.044)	(0.047)
Merged	-0.211+	-0.241
	(0.111)	(0.162)
Post-merger	-0.089	0.102
	(0.159)	(0.212)
Merged × Post-merger	-0.078	0.080
	(0.129)	(0.189)
Common clients		-0.578*
		(0.212)
Common clients × merged		0.436+
		(0.218)
Common clients × post-merger		0.410*
		(0.185)
Common clients × merged × post-merger		-0.455*
		(0.229)
Year fixed effects	YES	YES
Case-control group fixed effects	YES	YES
Observations	1097	1097
R-Squared	0.72	0.72

Clustered standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$