GEOGRAPHIC OVERLAP AND ACQUISITION PAIRING

Zhuo Chen
Jones Graduate School of Business
Rice University
6100 Main Street
Houston, TX 77005
Email: zc23@rice.edu

Prashant Kale
Jones Graduate School of Business
Rice University
6100 Main Street
Houston, TX 77005
Email: Prashant.Kale@rice.edu

Robert E. Hoskisson
Jones Graduate School of Business
Rice University
6100 Main Street
Houston, TX 77005
Email: robert.hoskisson@rice.edu

September 25, 2017

Key words: geographic overlap, acquisition, target selection, information asymmetry

ABSTRACT

Research summary: This study examines the role of geographic factors in explaining acquisition pairing using a novel conditional logic methodology. Drawing from information asymmetry arguments regarding acquisition decisions, we theorize that geographic overlap between the acquirer and potential targets' businesses and operations enables the acquirer to collect more information about the potential target through its multiple business operations that are geographically proximate. We also demonstrate moderating boundary conditions. In

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/smj.2742

particular, we examine acquiring firm characteristics, acquiring firm size and geographic dispersion, which both weaken the relationship between geographic overlap and acquisition pairing. Likewise, we examine two dyadic distance moderators, geographic distance and product dissimilarity, both of which increase information asymmetry between the acquirer and potential targets, which increases the effect of geographic overlap in facilitating acquisition pairing.

Managerial summary: Firms pursuing acquisition activities face severe information asymmetry when evaluating potential targets. This study investigates how acquiring firms leverage geographic conditions to overcome information asymmetry and choose targets that they can better evaluate. We find that acquirers are more likely to choose targets which have subsidiaries or business operations overlapping in the same states as the acquirers themselves. This is particular true for small acquirers which lack resources and capabilities to seek external assistance, and acquirers which have business operations in more concentrated locations. We also find that acquiring targets with geographically overlapped business operations is especially salient when the target's headquarters is distantly located from the acquirer or when the target offers dissimilar products from the acquirer.

An important issue for merger and acquisition (M&A) research is to understand how acquirers choose their respective targets (Baum, Li, and Usher, 2000; Bena and Li, 2014; Capron and Shen, 2007; Chakrabarti and Mitchell, 2013; Schildt and Laamanen, 2006). When firms seek external resources through M&As, they are often constrained by a lack of information and knowledge in properly evaluating the assets and abilities of potential targets. Information regarding the target's financial and strategic conditions is asymmetrically distributed between buyers and sellers (Ragozzino and Reuer, 2011), and it is expensive for buyers to conduct research to fully understand each aspect of a prospective target (Stiglitz, 2000). Additionally, even if the target is willing to disclose information to the potential acquirer, such information may not be credible (Akerlof, 1970). As Reuer (2005) notes,

> This is because sellers have natural incentives to inflate their representation of the quality of the offering in order to command a higher sale price, while acquirers already assume that sellers are presenting their best face. (p. 15)

Therefore, such information asymmetry between acquirers and their prospective targets creates barriers in the pre-acquisition evaluation process and the acquiring firm needs to rely on internal or external channels to overcome it.

Our study focuses on the newly increased attention scholars are devoting to understanding the role of geographic factors (Chakrabarti and Mitchell, 2013, 2016; McCann, Reuer, and Lahiri, 2016; Ragozzino and Reuer, 2011) in reducing information asymmetry and thereby explaining the rate of acquisition pairing. Acquisition pairing refers to the final consummation of an acquisition between two parties. In order for this to happen, the acquiring firm should first have a rough idea of what type of targets they are interested in and that such potential targets fall into their choice set of targets. Second, the acquiring firm will try to collect information about each potential target. The more information the acquiring firm successfully obtains for that particular target, the better evaluation the acquiring firm can perform, and the more likely acquisition pairing will occur. We argue that information asymmetry is more salient in the second stage because it requires much more information to fully understand a potential target than simply to know its existence, and it is harder to find such detailed information. Extant studies noted above generally suggest that if the headquarters (HQ) of the acquirer and target are geographically proximate, it is easier for the acquirer to collect required information about that target that, in turn, leads to a higher likelihood of acquisition pairing.

In this paper, we extend this research stream in several important ways. From a theoretical standpoint we argue that while the distance between the acquiring and target firms' HQ might be useful in explaining acquisition pairing, other geographical factors might also be important. First, we propose that geographical overlap between the two firms' operations and activities would increase the likelihood of acquisition pairing. Geographical overlap refers to the extent to which the business operations and activities [beyond the HQ] of the concerned firms overlap in different geographies.[1] The formal or informal interactions that occur between these overlapping operations of the respective acquirer and target firms enable a wide array of information flow (Ramos and Shaver, 2013). This overlap would help reduce information asymmetry between the acquirer and target and facilitate M&A incidence.

Second, although examining the effect of geographic overlap contributes to the literature on asymmetric information, we explore boundary conditions of our main hypothesis by investigating two "acquiring firm characteristics" as well as two "dyad-specific characteristics between the acquiring firm and potential targets" that influence the effectiveness of geographic overlap in impacting acquisition pairing. Because acquiring firms are taking the most risk in

[1] In this study, we only focus on the geographic distribution of a firm's business activities within the U.S, although we control for geographic diversification.

regards to information asymmetry we examine how two acquiring firm characteristics, acquiring firm size and geographic dispersion, moderate the impact of geographical overlap on acquisition pairing. While collecting information from overlapped geographic markets is useful for acquiring firms' learning about potential targets, this avenue is especially important for smaller acquirers that may lack sufficient resources to seek external assistance in evaluating potential targets. The extent to which the acquiring firm is geographically dispersed in terms of its own operations will also impact acquisition pairing. If the acquiring firm's operations and units are more widely dispersed across different locations, it becomes more complex and difficult for its HQ to collect relevant information about likely targets from those dispersed units. Such acquiring firm dispersion, in turn, will adversely influence some of the informational advantages that potentially exist due to the geographically overlapping operations between the acquirer and potential targets and thereby proportionally reduce the likelihood of acquisition pairing.

In regards to dyadic moderators between acquirer and targets, we examine two types of distance: (1) geographic distance between the respective HQ of the two concerned firms, and (2) product dissimilarity between them. In particular, we suggest that the effect of geographic overlap in reducing information asymmetry will be more pronounced if the merging firms are headquartered further apart. This hypothesis and the associated analysis are important because it has the potential to show how geographic overlap can enhance our understanding about what drives acquisition pairing beyond the impact of dyadic HQ distance as studied in previous research (e.g., Chakrabarti and Mitchell, 2013, 2016). Likewise, when the acquiring and target offer more dissimilar products, information asymmetry tends to be more salient. Under such conditions, the effectiveness of geographic overlap in reducing asymmetric information is enhanced and thus facilitates acquisition pairing.

By highlighting the role of geographic overlap, we attempt to join the strategic geography literature with information economics. We emphasize that information asymmetry between the acquiring and target firms is not only impacted by the direct information exchange between the HQ of the two firms (as proposed by prior research), but also by the exchange of information across their respective lower organization levels that overlap geographically, as well as by the internal transfer of that information between such units and the acquiring firm's HQ. Overall, our findings suggest that geographic overlap is an underexplored aspect to overcome information asymmetry especially when firms seek complementary assets by acquiring distant and dissimilar targets.

Empirically, we test our hypotheses in the U.S. context. The majority of previous studies, especially in the international business literature, base their measures of firm geographic areas using international data. However, this excludes local firms that do not have international operations. Moreover, international acquisitions are not only driven by informational consideration, but also by institutional context. Thus, in our study we focus only on domestic U.S. acquisitions. In the U.S., although the role of institutions may be critical, institutional influence may largely be less salient because generally strong institutions support the effective functioning of the market mechanism (Meyer *et al*., 2009). Given the differences in cultures, laws and regulations and the sheer distances between areas of the U.S., we believe that operating in the same states would provide informational advantage for the acquiring firm to better evaluate the target of interest. From a methodological standpoint, our approach takes into account potential acquisitions that did not occur. To identify such potential acquisitions, we conduct a matching procedure. We also advance prior research by using a conditional logit model to explore the acquisition pairing. First, this model allows us to simultaneously control for the target firm choice while examining the acquiring firm choice. Second, this technique allows us to avoid estimation bias by accounting for dependency among observations which comes from the fact that when one acquirer-target pair forms, it prevents other acquirer-target pairs in the same acquisition opportunity from forming.

THEORY AND HYPOTHESES

The theoretical foundation of this study rests on information asymmetry and strategic geography literature. In his seminal work, Akerlof (1970) explained how information asymmetry leads to failure in the used-car market. Analogously, the M&A market faces the same problem. On the one hand, firms searching for acquisition targets have incomplete information about the growth prospects, asset qualities, key technologies, corporate cultures, and other detailed aspects of prospective targets (Reuer, 2005; Zenger, 2013). Such information is critical in evaluating the strategic fit between the acquirer and target, which has been shown to have a substantial impact on acquisition performance (Haspeslagh and Jemison, 1991). While information on some aspects, such as financial information, is publicly available, information on others, such as corporate cultures and human capital, is not (Cartwright and Cooper, 1993). At the same time, targets also have an incentive to inflate the value of their assets to attract buyers and receive a higher acquisition premium (Anagnostopoulou and Tsekrekos, 2015; Ragozzino and Reuer, 2011). Such asymmetrically distributed information between the acquiring and target firms may often prevent the consummation of transactions that might have made strategic and financial sense.

Scholars in strategic management and finance draw upon the strategic geography literature to understand how acquiring firms overcome information disadvantages to evaluate acquisition opportunities. Specifically, they argue and show that acquirers tend to focus on targets with nearby HQ, as geographic proximity facilitates information collection and transfer and thereby reduces information asymmetry (Chakrabarti and Mitchell, 2013; Hannan and Rhoades, 1987; Schildt and Laamanen, 2006). With a target HQ that is more distant, acquiring firms have more physical and cognitive constraints, as well as limited resources, to collect information. Other research suggests that firms whose HQ are located in the same cluster prefer acquisition over alliance, because sharing a cluster location reduces information asymmetry and allows the acquiring firm to learn more about the target's resources (McCann *et al.*, 2016).

Geographic overlap and acquisition pairing

Simply focusing on the location of a firm's HQ does not allow us to account for information that is potentially available at lower-level operating units of an organization, which are often based in geographical locations that are different from that of the HQ. García and Norli (2012) show that from 1994 to 2008, the average U.S. public firm has business operations located in a minimum of 7.1 states and a maximum of 9.6 states. As such, acquiring firms could have access to high levels of information about potential targets from their own operating units present in different locations, besides the information available at the HQ. To address this research gap, we theorize that the preexisting level of geographic overlap between two firms' operations and activities facilitates target evaluation and thereby acquisition pairing in three ways.

First, the higher the geographic overlap between two firms, the larger the volume of information that will be exchanged. Since each geographic market can contribute some unique information associated with that specific geography, interacting with the prospective target in multiple geographic markets increases the total volume of information that could be collected by the acquirer. The second benefit of sharing multiple geographic markets is the existence of common local stakeholders and investors who help with information dissemination in each overlapping market. Valuable information about a particular firm often comes from employees, customers, suppliers, and local communities, because firms tend to maintain a close relationship with these stakeholders (Barringer and Harrison, 2000). First, the acquiring firm might make an “outside-in” analysis to evaluate its potential targets by talking to past members of the target organization, interviewing common suppliers, customers, industry observers and analysts (Fubini, 2014). Location in the same geographic market provides easier access for the acquiring firm to reach out to these stakeholders. Second, acquiring firms may benefit from information spillover during the process of managing their own stakeholders if the acquiring firms have business operations in the same areas as the potential target firms (Dorata, 2012). As stakeholder theory suggests, when companies set strategic directions, they should take into consideration communication with their stakeholders using surveys, the public record, and interviews with internal boundary spanners who are stakeholder experts (Chapter 4 in Freeman, 2010). Given that the acquiring firm and the target firm are located in overlapping geographic areas, the acquirer’s stakeholders may have interactions with the target firm’s stakeholders; thus, by virtue of their roles and responsibilities the former will bring that information into the acquiring firm. For example, people employed in the same geographic area may be members of the same local business associations and get to know more about each other’s companies. Such interaction may serve as a way of transferring information about one company to another.

Moreover, geographic overlap helps to reduce the information asymmetry that comes from assessing the quality of collected information. As previously noted, in order to attract more acquiring firms and command a higher acquisition premium, a target firm could have an incentive to “window dress” its assets. Hence, obtaining information from multiple geographies enables the acquiring firm to take a multi-prospective examination of the prospective target and have a more accurate grasp of the nature of the target (Beckman and Haunschild, 2002; Haunschild and Sullivan, 2002). For example, organizational units associated with different geographical areas may be responsible for distinct functions. The R&D department could help to assess the technological aspects of the target, while a distribution department could help to evaluate the target's marketing resources.

With higher geographic overlap in operations and activities, it follows that the acquirer would face less information asymmetry relative to understanding and assessing the potential target and thereby increase the possibility of acquisition pairing. Thus,

H1: The greater the geographic overlap between the acquirer and potential target firm, the greater the likelihood of acquisition pairing.

While geographic overlap facilitates acquisition pairing, the extent to which geographic overlap reduces information asymmetry depends on the certain preexisting attributes of the acquiring firm as well as the predetermined level of dyadic aspects between the acquiring firm and its potential targets. Thus, in the following sections, we examine these aspects to highlight some of the boundary conditions for our theory.

Acquiring firm characteristic moderators: acquirer size and geographic dispersion

Admittedly, acquiring firms differ in their capabilities to collect information. Thus, the extent to which geographic overlap is an important avenue to reduce information asymmetry would vary based on these differences. We believe the relationship between geographic overlap and acquisition pairing is more pronounced for small acquiring firms than for big firms. First, big firms have more resources and connections to conduct due diligence on potential targets. For example, big firms are more likely to establish an internal business development group with expertise to search for information about possible targets and thereby evaluate possible synergies (Triandis, 1999). Second, besides internal capabilities, big firms also have more financial support to seek external assistance. For example, some acquiring firms may be able to hire prestigious investment banks with highly capable analysts to help with information search and are better equipped to screen and evaluate potential targets (Sleptsov, Anand, and Vasudeva, 2013). Given that small acquiring firms have fewer alternative options and rely more on the capabilities of the operating managers, the preexisting level of geographic overlap as a means to reduce information asymmetry has more of an effect for these firms relative to larger firms. Following this logic, we hypothesize:

> *H2: The size of the acquiring firm will negatively moderate the relationship between geographic overlap and acquisition pairing, such that if the acquirer is large, the positive relationship between geographic overlap and acquisition pairing will be weaker.*

Besides information collection, it is also essential to consider the firm's capability of integrating information that has been collected in different parts of the organization. The strategic geography literature suggests that geographic dispersion plays an important role in information transfer and aggregation (Argote, 1999). By geographic dispersion, we mean the extent to which a firm's internal business activities are distributed across multiple geographic areas.

We argue earlier that geographic dispersion of the acquiring firm highlights the information complexity an acquirer's HQ needs to evaluate potential targets, and, as a result, undermines the otherwise salient informational advantages resulting from geographic overlap. Specifically, if an acquirer's business operations are concentrated in just a few locations, it is easier for the acquirer's HQ to coordinate information across operational units, and thereby the information about the potential target drawn from the overlapping markets will be effectively transferred. In contrast, if an acquirer's business operations are highly dispersed, the acquirer's HQ is faced with a more complex information-processing problem. Given that the efficiency of information transfer declines as the firm becomes more geographically dispersed (Audia, Sorenson, and Hage, 2001; Bernile, Kumar, and Sulaeman, 2015), it is harder for the acquirer's HQ to fully aggregate and absorb all of the inward flow of information. However, during the acquisition pre-evaluation period, the value of information depreciates quickly (Chakrabarti and Mitchell, 2013), thus geographic dispersion is likely to discount the value of information resulting from overlap. Also, geographic dispersion requires additional layers of managerial staff for coordination and control, which complicates the acquiring firm's organizational structures and dampens intra-organizational information sharing due to decentralization (Schleimer and Pedersen, 2014). Thus, we propose the following hypothesis:

> *H3: The geographic dispersion of the acquiring firm will negatively moderate the relationship between geographic overlap and acquisition pairing, such that if the geographic dispersion of the acquirer is high, the positive relationship between geographic overlap and acquisition pairing will be weaker.*

Dyadic characteristic moderators: geographic distance and product dissimilarity

Acquiring external assets is an important avenue for companies to grow both in scale and in scope, and useful assets may reside in geographically distant contexts. However, due to organizational and cognitive constraints (Cyert and March, 1963; Nelson and Winter, 1982), firms may be limited geographically in accessing such useful resources and end up buying targets that are located nearby (Chakrabarti and Mitchell, 2013; McCann *et al.*, 2016). Prior studies have identified mechanisms that can serve as bridges to distant contexts. For example, Rosenkopf and Almeida (2003) find that employee mobility facilitates interfirm knowledge flows regardless of geographic proximity. In this paper, we have suggested another avenue for reducing information asymmetry of evaluating distant resources: searching through the company's lower level operations that are located near those of the focal resources of interest. Specifically, we argue that when the geographical distance between the target and the acquiring firm HQs is large, the acquiring firm can still manage to reduce information asymmetry if it has business operations that overlap with either the target HQ or the target's lower level operations. In other words, geographic overlap between the acquirer and target plays a more important role in reducing information asymmetry when the acquirer is interested in taking over a target whose HQ is more remote from its own. This argument is critical because it potentially demonstrates the importance of geographic overlap in impacting acquisition pairing compared to past research that only considers the direct impact of HQ distance between the acquirer and target on acquisition pairing (e.g., Chakrabarti and Mitchell, 2013, 2016). Therefore, we propose the following hypothesis:

> *H4: The geographic distance between the HQs of the acquiring and target firms will positively moderate the relationship between geographic overlap and acquisition pairing, such that if the geographic distance is large, the positive relationship between geographic overlap and acquisition pairing will be stronger.*

The impact of geographic overlap on acquisition pairing is also contingent upon the dyadic nature of the businesses of the two firms involved in a potential acquisition. When the acquiring firm wants to acquire a target that offers dissimilar products, information asymmetry will be more salient, as the acquiring firm is not familiar with the target firm's business operations and environment. Overlapping geographic markets, in this case, provide an important avenue for the acquirer to learn about the potential target, which helps to mitigate information asymmetry. Conversely, acquirers interested in buying targets with similar or overlapping businesses face less information asymmetry because they are more likely to share similar resource bases, have similar inputs, implement similar technology, and target similar customers (Wang and Zajac, 2007). Therefore, the product similarity between the acquirer and the potential target naturally generates knowledge about the other, and hence the acquirer is more likely to be able to evaluate the assets and the ability of the target. This information is potentially substitutive for information that might be obtained through geographic overlap. Thus, we expect geographic overlap to have a stronger impact on acquisition pairing when product dissimilarity between the acquirer and potential target is high. Product dissimilarity may be present when an acquiring firms endeavors to take over a "complementary" target (Harrison *et al.*, 1991), whereby learning becomes more essential (Makri, Hitt, and Lane, 2010). Complementarity occurs when two firms possess non-overlapping knowledge or capabilities that, when combined, result in incremental value or advantage. However, it is more difficult for the acquiring firm to price such an acquisition due to higher learning distance between the acquiring and target firms' assets and capabilities, which results in more information asymmetry (Hoskisson and Busenitz, 2002). As such, when product dissimilarity exists between acquiring and possible target firms, geographic overlap will likely enhance acquisition pairing.

> *H5: Product dissimilarity will positively moderate the relationship between geographic overlap and acquisition pairing, such that if the two firms have high product dissimilarity, the positive relationship between geographic overlap and acquisition pairing will be stronger.*

METHODS

Research design

This study focuses on whether geographic overlap is positively associated with acquisition pairing and the factors that may moderate this relationship. This requires modeling a choice problem described by (a) the objects of choice and sets of alternatives available to the decision-makers; (b) the attributes of each alternative; and (c) the model of choice behavior (McFadden, 1973). Although our theoretical arguments are centered on the acquiring firm choice, in practice, targets may face multiple bidders simultaneously and must choose the one that best meets their needs. Our empirical approach is carefully designed as a test for the hypotheses by controlling for the target firm choice. The objects of choice are firm pairs that have the potential to form acquisitions rather than simply the alternative targets available to the acquirer. However, not all possible combinations of firms are "at risk" of forming an acquisition. To construct the meaningful alternatives within each choice set, we first compiled a sample of acquisitions and view each acquisition as a realization of an opportunity. For each acquisition that is actually realized, we then identified a set of potential firm pairs that may compete for such an acquisition opportunity. We describe the specific identification process in the next section.

Acquisition pairing sample and data

Drawing from Thomson Reuters' Security Data Corporation (SDC) database, we identified domestic M&As in the U.S. market announced between January 1, 1997 and December 31, 2008[2] that satisfy the following requirements: (a) the transactions were complete; (b) the deals were coded as a merger, an acquisition, an acquisition of majority interest, or an acquisition of assets; (c) the acquirer owned zero percent of the target firm prior to the bid, sought to own more than 50 percent of the target firm, and owned more than 90 percent of the target firm after the deal was closed; (d) neither the acquirer nor the target firm was from the financial sector (SIC 6000-6999);[3] and (e) the information on variables used in this study is publicly available. We were able to find 1,936 M&As that meet all the foregoing requirements, where the corresponding 1,936 acquirer-target pairs constitute the sample of chosen alternatives.

We then extended our data set to include the potential acquirer-target pairs not chosen. To identify such pairs, we conducted a matching procedure. Analyzing choice problems based on matched samples has been well received in the strategy literature (cf. Chakrabarti and Mitchell, 2013; McCann *et al.*, 2016; Reuer and Lahiri, 2014). Specifically, we performed the following procedure to match for potential targets in each acquisition opportunity. First, the potential

[2] Our sample ends by 2008 due to data limitations associated with our geographic measurement.
[3] Financial services industries have different asset structures from other industries and are highly regulated.

targets needed to satisfy two conditions: first, an industry related condition, whereby the target should operate in the same industry[4] as the actual acquired firm in the year of the focal acquisition, as acquisitions tend to cluster in time and by industry (Harford, 2005); and second, an acquisition related condition, whereby the target is eventually acquired within five years of the focal acquisition. The latter acquisition condition ensured that the potential targets are active players in the M&A markets. Second, we ran a probit regression using size, market-to-book ratios (M/B), returns on assets (ROA), and cash balance[5] to predict the likelihood of a firm being a target, which is defined as the propensity score. The regression is reported in the first column of Table 1. We assume that firms that have similar estimated propensity scores as the actual target fall into the same target choice set. Third, we then ranked all potential targets in an acquisition opportunity (selected by the industry and acquisition conditions), based on the closeness of their respective propensity score to the propensity score of the actual target. We picked the top three[6] to be the potential targets for that particular acquisition opportunity.

Additionally, we applied a similar procedure and criteria to match for potential acquirers. First, potential buyers should be operating in the same industry as the actual buyer in the year of the focal acquisition, and should have participated in acquisition activities in the five years subsequent to the focal acquisition. Second, we ran a probit regression using size, M/B, ROA and cash balance to predict the likelihood of a firm being an acquirer, which is the propensity score. The propensity score regression is reported in the second column of Table 1. Third, we ranked all potential acquirers in an acquisition opportunity (selected by the first criterion), based

[4] We used two-digit SIC industry.
[5] Prior studies have suggested that such firm characteristics and financials are important components considered by acquiring firms (Bena and Li, 2014).
[6] We also tried five matches in the additional analyses as a robustness check and obtained similar results.

on the closeness of their respective propensity score to the propensity score of the actual acquirer, and picked the top three to be the potential buyers.

As a result, we had one actual acquirer-target pair and six overall potential acquirer-target pairs within each choice set: three potential targets paired with the actual acquirer and three potential acquirers paired with the actual target. We excluded those completed acquisitions in which we could not find any matches. We further excluded 61 potential acquirer-target dyads where the acquirer and the target were associated with the same parent. Our final sample thus consisted of 1,616 actual acquirer-target pairs and 10,408 potential acquirer-target dyads.

Insert Table 1 about here

In addition to the SDC database, we drew on several other data sources to measure the variables. To measure geographical overlap, the primary source of data is Form 10-K, an annual report required by the U.S. Securities and Exchange Commission (SEC) that provides a comprehensive summary of a company's financial performance and operations. This source allows us to identify the geographic distribution of firms' business activities across U.S. states. Information about a firm's state-level operations is likely disclosed in the following sections of Form 10-K: "Item 1: Business," "Item 2: Properties," "Item 6: Consolidated Financial Data," and "Item 7: Management's Discussion and Analysis." Following prior research (García and Norli, 2012a, 2012b), we used a computer program to access the electronic filing system (EDGAR) used by the SEC and extracted state names from Form 10-K as well as a paragraph or several sentences where a U.S. state name is mentioned. Data obtained this way are considered to be more detailed and comprehensive than the Compustat Geographic Segment Data (Cohen, Malloy, and Pomorski, 2012). Further, to validate these data two research analysts conducted a analysis by reading the extracted information and determine whether the state mentions in the

10-K are indeed related to business activity locations. The analysts used the following criteria to make the evaluation: (1) whether any words like manufacturing, facilities, subunits, branch, operations, distribution channels, business unit, and sales department are mentioned; (2) whether the firm is headquartered in the state; and (3) whether the firm acquired a firm/target that is located in the state. Because of the large volume of data, it is impossible to manually check every single state mention; thus, we randomly selected 100 firm-years that refer to 760 state mentions. The analysts independently checked these state mentions and arrived at an interrater reliability of 92.89 percent. Only 6 percent are rated as not related to business activities; some systematic errors seemed to occur in the case of New York, Washington, and Delaware (e.g., some firms are listed in New York Stock Exchange but do not necessarily have business activities in the state of New York. Also, many firms are incorporated in Delaware, but do not operate there. In addition, some of the state mentions of Washington are indeed Washington D.C). To eliminate these errors, we dropped these states in the main analyses.

Data from Form 10-K was also used to construct the “product dissimilarity” measure as the 10-K also contains a product description section in its Item 1 or Item 1A that describes the significant products a firm offers. On the form, this information is legally required to be accurate and updated in the current fiscal year (Shi, Zhang, and Hoskisson, 2017). Hoberg and Phillips (2010) applied a text-based analysis of firms’ 10-K filings to determine product similarity between firms. Such data have several advantages over the SIC industry code classification. First, it is based on product descriptions and takes into consideration the level of corporate diversification. Second, given that firms introduce and discontinue products, as well as enter and exit the industry space over time, these data take into account product and industry change by incorporating the changing nature of the product markets.

The second source of data is Compustat, which provides historical data on firms' fundamentals. We also collected data on some controls from Bloomberg.

Variables and measurement

The unit of analysis is each acquisition opportunity, which consists of an actual acquirer-target pair and the corresponding potential acquirer-target dyads. We measured dyad- and firm-level variables for each unit of analysis to assess the probability that two firms will strike a deal.

Acquisition pairing. The dependent variable is a dyad-level variable that captures the likelihood of an acquisition between two firms. We use a 1–0 dummy to indicate whether the two firms within a dyad formed an acquisition in a given year. Specifically, we code this variable 1 for those dyads in which the two parties constitute an actual acquirer-target pair, and 0 otherwise. We measure the dependent variable for year t, and the independent variables and control variables at time $t - 1$.

Geographic overlap. The main independent variable of this study is the extent to which a potential acquirer and a potential target have business operations in overlapping geographic markets. As previously explained, we collected information from 10-Ks on the way in which firms' business activities are distributed across states. We use this data to operationalize the geographic overlap between firms i and j as the number of states in which both firm i and firm j have business operations. For example, if firm A has business operations in California, Illinois, and Texas, and firm B has business operations in California, Illinois, and Michigan, the geographic overlap between Firm A and Firm B is two, because they both have business operations in California and Illinois. The average geographic overlap of firm pairs in our sample is 2, ranging from 0 to 35.

Acquirer size. We measure acquirer size as the natural logarithm of the acquirer's total assets. We also alternatively measure acquirer size as the natural logarithm of the acquirer's total number of employees as part of the robustness checks.

Acquirer geographic dispersion. We use a 1–0 dummy to measure whether an acquiring firm's business operations are geographically dispersed in a given year. Specifically, it is equal to 1 if the number of states where the firm has business activities is greater than the sample median, and 0 otherwise.

Geographic distance. We calculate the actual miles between the acquirer's and target's HQ using the following formula.

(1) $$\mathrm{Miles}_{\mathrm{at}} = \mathrm{C}\{\cos^{-1}[\sin(\mathrm{lat}_{\mathrm{a}})\sin(\mathrm{lat}_{\mathrm{t}}) + \cos(\mathrm{lat}_{\mathrm{a}})\cos(\mathrm{lat}_{\mathrm{t}})\cos(|\mathrm{long}_{\mathrm{a}} - \mathrm{long}_{\mathrm{t}}|)]\},$$

where *lat* and *long* refer to the latitude and longitude of the acquiring and target firm's HQ locations, respectively.[7] *C* is a constant that converts the result to miles on the surface of the earth; we used 3,437. We then apply a natural log transformation of actual miles. To facilitate the interpretation of the moderating effect, we operationalize the geographic distance as a 0–1 dummy where 1 means the log distance between the two firms' HQs is larger than the sample median, and 0 otherwise. As a robustness check, we also use the actual length between the two firms' HQs to measure geographic distance.

Product dissimilarity. As we previously explained in the data section, Hoberg and Phillips (2010) developed a measure of product similarity based on the Form 10-K product description. Basically, they built a dictionary by creating a list of unique words (for example, "N" words) used in all product descriptions and then constructed a binary N-vector for each firm to characterize its word usage. Product similarity between firm *i* and firm *j* is measured by the multiplicative product of firm *i* and firm *j*'s normalized N-vectors. The measure is continuous

[7] The latitude and longitude are determined based on the zip code of the firm's headquarters.

between 0 and 1, in which 1 represents high product similarity. We adopt the same approach to measure product similarity between acquirer-target firms in our study and then estimate "product dissimilarity" for each observation by simply multiplying the similarity measure by -1.

Controls. We control for the presence of financial advisors, which may help to reduce information asymmetry, because such intermediaries may work as catalysts in the identification, valuation, and selection of appropriate targets (Sleptsov *et al*., 2013). To create these controls (for both acquirer and target), we collected data on whether an acquiring firm or a target firm used any investment bank in a particular acquisition and the name of those banks from the SDC. We further collected data on the ranking of each bank in the year when the acquisition occurred based on the Bloomberg M&A League Table. Not only does this variable control for whether an investment bank was involved, it also controls for the prestige of the investment bank, which reflects the probable quality of the analysts performing due diligence. Accordingly, we generated a variable, *acquirer investment bank prestige*, to measure whether the bank used by the acquirer is among the top 10 investment banks of the year. This variable takes the value of 0 if the acquirer is not using any investment banks for the given acquisition, 1 if none of banks the acquirer is using is ranked top 10, and 2 if any of the banks the acquirer is using is ranked top 10. Similarly, *target investment bank prestige* equals to 0 if the target is not using any investment banks for the focal acquisition, 1 if none of banks the target is using is ranked top 10, and 2 if any of the banks the target is using is ranked top 10. For potential acquirers and targets, we assume the choice of financial advisors in the focal acquisition opportunity to be the same as their choice in the next acquisition they participated. This information is available because all potential acquirers and targets are active in the M&A market according to the matching procedure. For example, if firm *i* was matched as a potential acquirer in year 1, and firm *i*'s next deal is in year 3 using bank *j*, we assume firm *i* would also use bank *j* in year 1. We believe this is a valid assumption because the process of pre-acquisition search and identification is likely to start years before the actual acquisition.

We also control for whether the acquiring and target firm belong to the same 3-digit SIC industry; *3-digit SIC industry* is equal to 1 if they do, and 0 otherwise. *Prior acquisition experience* counts the number of acquisitions the acquirer has made before the focal acquisition. Given that firms with international operations may take a different view on domestic acquisitions as compared to firms that are only exposed to domestic markets, we control for firms' *internationalization*, which is computed as foreign sales[8] divided by the firm's total sales.

We also control for the following firm level variables. *Firm performance* is measured by earnings before interest, taxes, depreciation, and amortization scaled by total assets (*ROA*). *Leverage* is measured by total debt scaled by total assets. *Cash holdings* is measured by cash and short-term investment scaled by total assets. *Market-to-book (M/B)* is measured by the market value of common equity scaled by the book value of common equity. Using the Compustat product segment data, we measure *Diversification* as the weighted average of the proportion of total sales in each segment, in which the weight is the natural logarithm of the inverse of the total sales proportion in each segment (Raghunathan, 1995). *Firm size* is measured by the natural logarithm of the firm's total assets. Given that acquirer firm size is a variable of interest, we only control for target firm size.

We further control for deal-fixed effects. Since there is no time difference within a choice set (acquisition opportunity), we do not need to control for time-fixed effects. All ratios are winsorized at 1 percent and 99 percent of their empirical distribution to reduce the effect of

[8] Foreign sales are calculated by aggregating the Compustat geographic segment data.

outlier observations.

Model specification

Given the dichotomous nature of the dependent variable, a dichotomous choice framework (i.e., logit or probit) seems to be a good fit. The drawback of a dichotomous choice framework (i.e., logit or probit), which has been mostly adopted by prior research, is that each potential acquirer-target pair in an acquisition opportunity enters the estimation as a separate case. Yet, this is clearly not true in our case because when one acquirer-target pair forms, it prevents other acquirer-target pairs in the same acquisition opportunity from forming.

Therefore, we turn to a maximum likelihood model that more directly captures the structure of the choice problem (cf. Martin and Stevenson, 2001). Specifically, we model acquisition pairing as an unordered discrete choice problem in which each acquisition opportunity (not each potential acquirer-target pair) represents one case and the set of discrete alternatives includes the actual acquirer-target pair and potential combinations of acquirers and targets that might compete for the focal acquisition opportunity. The particular specification of the multinomial model we adopt is the conditional logit model (McFadden, 1973). A conditional logit model is the statistical model of preference in research on foreign entry location choice (Belderbos, Olffen, and Zou, 2011; Chang and Park, 2005; Henisz and Delios, 2001). This model is a good fit for us because it maps characteristics of a choice candidate to the probability chosen from among a set of alternatives. The formal representation of the conditional models we test is given in Eq. (2):

(2) $$p_t[x = (i^*, j^*) | R_{t-1}, A_{t-1}, T_{t-1}] = \frac{\exp(\beta_1 R_{i^*,j^*,t-1} + \beta_2 A_{i^*,t-1} + \beta_3 T_{j^*,t-1})}{\sum_{i,j} \exp(\beta_1 R_{i,j,t-1} + \beta_2 A_{i,t-1} + \beta_3 T_{j,t-1})},$$

where

$p_t[x = (i^*, j^*) | R_{t-1}, A_{t-1}, T_{t-1}]$ is the odds of acquirer-target pair (i^*, j^*), rather than any other potential pairs, to realize an acquisition opportunity at time *t* given the attributes of all choice candidates at $t - 1$; $R_{i,j,t-1}$ is a vector of relational features between acquirer *i* and target *j* at time $t - 1$, in which geographic overlap, geographic distance, and product dissimilarity are three of the elements; $A_{i,t-1}$ is a vector of acquirer *i* characteristics, in which acquirer size and acquirer geographic dispersion are two of the elements; and $T_{j,t-1}$ is a vector of target *j* characteristics.

In the conditional logit specification, the unit of analysis is the choice set (in our case, the acquisition opportunity). The advantage of this model is that it allows the dependent variable to have a multinomial distribution that resolves the deterministic dependence among alternatives within a choice set; that is, only one pair of acquirer-target gets formed in each acquisition opportunity.

RESULTS

Table 2 includes summary statistics of the acquiring and target firms and their industry- and propensity score-matched counterparts. Table 3 provides the correlations between each pair of variables.

Insert Table 2 about here

Insert Table 3 about here

Regression analysis

Using our conditional logit regression, Model 1 of Table 4 is a baseline model that includes all control variables that could potentially affect acquisition pairing or geographic overlap. The results of this model provide consistent findings with prior studies, but with the use of a cross-industry sample. Specifically, the coefficient associated with geographic distance is negative (b =

-0.442) with a confidence interval [- 0.571, - 0.314] at the 99 percent significance level. This verifies the conclusion of existing research based on a sample of chemical manufacturing firms in which acquisition tends to occur between two firms with HQ that are located near each other (Chakrabarti and Mitchell, 2013).

Insert Table 4 about here

H1 states that higher geographic overlap between the acquiring and target firms will be associated with a higher likelihood of striking a deal. As seen in Model 2 of Table 4, the coefficient associate with geographic overlap is positive (b = 0.040) with a 99 percent confidence interval [0.010, 0.070], meaning the estimated coefficient falls into the interval [0.010, 0.070] at the 99 percent confidence level. H1 thus receives support. Given the nonlinearity of the model, the absolute value of the coefficient does not provide a direct sense of the substantive importance of the effect. Following prior studies (cf. Martin and Stevenson, 2010), we calculated the substantive effect of geographic overlap on acquisition pairing by examining the odds ratio[9] for different values of geographic overlap in the data. We defined low geographic overlap at the 25th percentile in the data (0) and high geographic overlap at the 75th percentile in the data (3). Therefore, the odds of acquisition pairing associated with a change from low geographic overlap to high geographic overlap is exp [(3 – 0) * 0.040] = 1.13 based on Model 2. This means that acquirer-target pairs with high geographic overlap are approximately 13 percent more likely to enter into an acquisition than acquirer-target pairs in which the two firms have a low level of geographic overlap. Thus, geographic overlap has a substantive impact on the probability acquisition pairing after controlling for the effect of proximate headquarters.

[9] The odds ratio is the exponentiated coefficients, which give the ratio by which the dependent variable changes for a unit change in an explanatory variable; that is, the effect is presented on a multiplicative scale (Buis, 2010).

Model 3 and Model 4 of Table 4 test the two firm-level moderators, H2 and H3. As seen in Model 3, the coefficient associated with the interaction between geographic overlap and acquirer firm size (H2) is negative (b = -0.021) with a confidence interval [-0.036, -0.007] at the 99 percent significant level. As seen in Model 4 of Table 3, the coefficient associated with the interaction between geographic overlap and acquirer geographic dispersion (H3) is negative (b = - 0.113) with a confidence interval [- 0.197, - 0.028] at the 99 percent significance level. Although interpreting the coefficients associated with interaction terms in nonlinear models is difficult, the direction of the coefficient does indicate the general direction of the effects on acquisition pairing—that is, a positive coefficient increases the probability of acquisition pairings that have the indicated characteristics and decreases the probability of those that do not.

Model 5 and Model 6 test the two moderators related to dyad-specific characteristics. H4 states that the geographic distance between the acquiring and target firms' HQ will positively moderate the association between geographic overlap and acquisition pairing. As seen in Model 5, the coefficient associated with the interaction between geographic overlap and geographic distance is positive (b = 0.063) with a confidence interval [0.022, 0.103] at the 99 percent significance level. H5 suggests that the positive relationship between geographic overlap and acquisition pairing will be stronger if the product dissimilarity is high. Model 6 indicates a positive coefficient associated with the interaction between geographic overlap and product dissimilarity (b = 1.090) with a confidence interval [0.610, 1.569] at the 99 percent significance level.

To further explore the magnitude of the interaction effect and investigate whether the moderating hypotheses are supported, we computed the implied coefficient associated with geographic overlap at different values of the moderators based on the full model (Model 7 in

Table 4). We also reported the change of odds ratio associated with the acquisition pairing when increasing the degree of geographic overlap between the acquiring and target firms from 0 to 3 because odds ratio has been shown to be a good way of interpreting interaction effects in terms of marginal effects in all types of logistic models (Buis, 2010). The four typical cases help in understanding the economic impacts of the moderators (see Table 5): (1) In case 1, fixing the level of acquirer geographic dispersion = 1, geographic distance = 0, and product dissimilarity = 0, we see that as the acquirer's firm size (in terms of natural log of assets) increases by 1 unit, the percentage change in odds associated with increasing geographic overlap decreases from 53.57 percent to 45.06 percent, indicating a substantive negative moderating effect due to the acquirer's firm size. (2) In case 2, fixing the level of acquirer size (in terms of natural log of assets) = 5, geographic distance = 1, and product dissimilarity = 0, we see that as the acquirer's geographic dispersion increases from "0 to 1," the percentage change in odds associated with the effect of geographic overlap on acquisition pairing decreases from 87.76 percent to 48.59 percent—which corroborates a negative moderating effect of acquirer geographic dispersion. (3) In case 3, if we consider a medium-sized acquiring firm (acquirer size in terms of logged assets = 7) that is geographically concentrated (so geographic dispersion = 0) and attempts to acquire a dissimilar target (so product dissimilarity = -0.1), we see that as the geographic distance increases from "0 to 1," the percentage change in odds associated with increasing geographic overlap significantly increases from 10.74 percent to 27.12 percent, which supports the positive moderating effect of geographic distance on the relationship between geographic overlap and acquisition paring. (4) Finally, in case 4, we considered a large firm (acquirer size in terms of logged assets = 8) that is geographically concentrated (so geographic dispersion = 0) and interested in a remote target (so geographic distance = 1). As product dissimilarity increases from “-0.1 to 0,” the percentage change in odds associated with the impact of geographic overlap on acquisition pairing increases from 20.08 percent to 58.25 percent, thus providing supporting evidence for the substantive positive moderating effect of product dissimilarity on the relationship between geographic overlap and acquisition pairing.

Insert Table 5 about here

ROBUSTNESS

Target-related boundary conditions

The extent to which geographic overlap helps with acquisition pairing also depends on the nature of the target because acquiring firms face different levels of information asymmetry when facing different types of targets. The most important distinction is whether the target is private or public as private targets have less disclosure and thereby create more information asymmetry for the acquiring firm. However, given that our sample includes target firms in which geographic overlap information is collected from what is available in their 10-K forms, all target firms in our sample are publicly listed firms. Therefore, we were not able to test this moderating effect directly. Following the same logic, we do find that geographic overlap has a stronger effect for targets that have recently become public (i.e., less than or equal to two years) on the premise that in so doing, they have relatively less information available in the public domain as compared to firms that are public for a much longer period and hence provide greater available information. The coefficient associated with the interaction between geographic overlap and newly publicly listed firms is positive ($b = 0.271$) and falls into the confidence interval of [0.035, 0.507] at the 95 percent significance level (we have not included the table with these results but can do so upon request). This suggests that the effect of geographic overlap on acquisition pairing is 31.13 percent higher for targets that have recently become public, which further corroborates our information asymmetry argument.

Alternative measures

In the main analysis, we measured acquirer firm size as the firm's total assets. Alternatively, we used the firm's total number of employees to measure acquirer firm size, which is also widely used in the strategy literature, as a robustness check. We reported the results in the second column of Table 6. We included the original model we used in the main analysis in the first column of Table 6 to facilitate comparison. As seen in the table, the coefficient associated with the interaction between geographic overlap and acquirer firm size measured by the total number of employees is negative (b = -0.022) with a confidence interval of [-0.037, -0.006] at the 99 percent significance level. This coefficient suggests that increasing the natural log of the number of employees by 1 unit, the odds associated with the impact of geographic overlap on acquisition pairing will decrease by about 2 percent. This is consistent with the original model. Moreover, in the main analysis, we operationalized geographic distance between acquiring and target firms' HQs as a dummy for interpretation purposes. Here, we also measured geographic distance as the actual length (natural log transformation of actual miles as calculated previously) as a robustness check. As seen in the third column of Table 6, the coefficient associated with the interaction between geographic overlap and geographic distance is positive (b = 0.12) with a confidence interval of [0.001, 0.023] at the 90 percent significance level, providing support that our main finding is robust.

Insert Table 6 about here

Alternative matching

Given that our empirical analysis is based on a matched sample, it is possible that our results are susceptible to the matching procedure implemented. As a robustness check, we conducted another set of matching procedures and then reran Model 7 in Table 4. First, we varied the number of matches to see whether the empirical findings are robust. We increased the number of matches by discovering up to five potential targets and acquirers based on the propensity score. As seen in the fourth column of Table 6, the coefficients and standard errors associated with geographic overlap and the three interactions are very close to those in the original model—that is, they have the same directional sign but with a slightly bigger magnitude. Therefore, we believe that the number of matches chosen do not affect our empirical results. We further modified the matching procedure by simply matching on size and redid the analyses. This is because propensity score matching may be sensitive to the variables included to calculate the propensity score. We reported the results in the last column of Table 6. As can be seen, both the directional sign and magnitude of the coefficients are very consistent with the original model, as well as the magnitude of the standard errors. Therefore, we conclude that the specific matching procedure does not drive our main results reported in Table 4.

DISCUSSION

This paper explains how geographic overlap between the acquiring and target firms' business activities has an impact on M&A incidence between the two parties and also provides empirical evidence. In so doing, we integrate the strategic geography literature and information economics to suggest that interacting with the prospective target in overlapping geographic markets helps to reduce information asymmetry between the acquirer and the target. Therefore, the acquirer is in a better position to evaluate the assets and abilities of the target firm and make better investment decisions. We further develop the argument that this effect is stronger if the acquiring firm is small because such firms lack the resources to develop internal business development groups or hire third parties to help with the search and rely more on overlapping geographic markets to collect information by operating managers. It is also weakened if the acquiring firm is geographically dispersed, as dispersion increases information complexity and thereby impedes the efficiency of information transfer across geographical areas. Moreover, the geographic overlap impact of acquisition pairing is stronger when the acquirer and target are headquartered remotely, as geographic distance increases the difficulty of search and thereby information asymmetry, or if the acquirer and target offer distinct products, as firms with dissimilar businesses do not have sufficient knowledge to understand each other and thus are confronted with a more severe information asymmetry problem.

This study makes several contributions to acquisition research as well as to the strategic geography literature. First, by introducing geographic overlap and dispersion into the M&A domain, we provide additional insight into how firms make acquisition choices. This insight also addresses the call by strategic management scholars to focus on the strategic importance of geography in corporate development (Sorenson and Baum, 2003). While prior work has mainly focused on the geographic distance between acquiring and target firms' HQ, we suggest that the mere distance between two parties' HQs does not allow us to account for the formal and informal information exchange process that takes place at lower levels of the organization, which is also likely to reduce information asymmetry and hence facilitate acquisition pairing. Our empirical findings suggest a significant economic impact of geographic overlap on acquisition pairing. Specifically, we find that acquirer-target dyads with high geographic overlap are approximately 13 percent more likely to strike a deal than acquirer-target pairs with low geographic overlap after controlling for the geographic distance between the two parties' HQ locations. This finding provides important managerial implications for firms in the M&A market. From the standpoint of acquiring firms, top managers in such firms should pay attention to the geographies where the firm has business operations in search of expansion opportunities.

We also examine the boundary conditions of joining economic geography and information economics. In particular, we examine how an acquiring firm's geographic dispersion mitigates the acquisition pairing effect of geographic overlap. Although extant literature has emphasized how geographic dispersion influences the focal firm's corporate development (Audia *et al.*, 2001; Gibson and Gibbs, 2006; Landier, Nair, and Wulf, 2009), our work extends the impact of geographic dispersion to the dyad level by linking geographic dispersion to how acquiring firms select acquisition targets. We emphasize that a firm's geographic arrangements not only influence its own behavior, but also presents implications for its relationship with other parties. We also examine how geographic distance and product dissimilarity create more potent cases for examining geographical overlap. When a firm looks to create complementarity through acquiring a distant or dissimilar target, our results suggest that geographical overlap is likely to be a more salient tool in helping to overcome the problem of information asymmetry.

This study also makes an empirical contribution to investigating choice problems in the management field. Most management studies concerning a choice problem adopt a dichotomous choice framework (e.g., employ probit or logit model), in which each choice alternative enters the estimation as a separate case. However, this dichotomous choice model is mis-specified when deterministic dependence exists among alternatives in the choice set. Such model misspecification will bias the estimation results and hence potentially invalidate the statistical inference. We propose a better way of modeling the choice problem by implementing a conditional logit specification. A conditional logit model allows us to assign a multinomial distribution to the dependent variable and structure the model in a way that the deterministic dependence will not bias our estimation. Moreover, we design our research to test the hypotheses on the acquirer's side by controlling for the choice of the acquirer and target simultaneously. In real-world practice, the acquirers are able to select the target that best meets their needs, and the target often faces bids from multiple acquirers. Without controlling for the target firm choice among potential acquiring firm bidders, the estimation might be biased toward the acquirer's preferences and thereby deviate from the true value.

This study has some limitations that provide avenues for future studies. First, we measure geographic overlap based on whether two firms have business operations in the same state. However, due to data limitations, we are unable to directly capture whether the interactive activities actually occur. Future research could use surveys to collect information about the actual relationship between the acquirer and target business operations within each geographical region. Second, although we have restricted our analysis to domestic acquisitions, our theoretical arguments may also be generalized to cross-border acquisitions. Future research could extend this study to an international context by constructing a proper measure of international geographic overlap. Third, this paper focuses on how geographic overlap can reduce information asymmetry in the pre-acquisition evaluation process. However, the information gathered may not all be positive. Although we argue that the acquiring firm is more likely to eventually choose targets they possess the most positive information about rather than targets that they know nothing about, future research could further examine how acquiring firms deal with different types of information to make acquisition decisions. Finally, it is possible that certain potential acquirers or targets were not captured using our matching assumptions. Future research can examine how acquiring firms narrow their target candidates by conducting field studies and looking into the actual pre-acquisition evaluation process.

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ACKNOWLEDGEMENT

We would like to note the feedback of the editor, Connie Helfat and to anonymous reviewers for their constructive help leading to improvements in our research and manuscript. We would also like to note the help of Wei Shi who suggested some of the data sources for this paper.

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Accepted Article

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Table 1. Propensity score matching regressions (a probit model)

	(1) DV equals 1 if the firm is a target in the focal year and 0 otherwise	(2) DV equals 1 if the firm is an acquirer in the focal year and 0 otherwise
Size	0.179	0.186
	(0.009)	(0.008)
ROA	-0.173	0.102
	(0.087)	(0.077)
M/B	-0.008	0.038
	(0.010)	(0.007)
Cash	0.009	-0.299
	(0.085)	(0.077)
Constant	-3.156	-3.056
	(0.066)	(0.056)
Observations	52,285	52,285
R-square (%)	8.42	9.46

Note: Robust standard errors clustered at firm-level in parentheses

Table 2. Summary statistics

Panel A: Acquirer characteristics	Acquirer			Potential acquirer		
	Mean	SD	Median	Mean	SD	Median
Geographic dispersion	0.43	0.50	0.00	0.45	0.50	0.00
Firm size	7.07	2.09	7.08	6.81	1.87	6.87
Investment bank prestige	0.69	0.85	0.00	0.74	0.87	0.00
ROA (%)	12.84	11.00	13.59	12.20	12.18	12.97
Cash (%)	16.81	19.80	8.25	17.25	20.23	8.11
Leverage (%)	20.83	19.55	17.41	20.28	19.30	17.41
M/B	4.03	9.21	2.76	4.30	8.39	2.74
Diversification	0.30	0.43	0.00	0.29	0.42	0.00
Prior acquisition experience	4.36	8.81	0.00	2.66	7.38	0.00
Internationalization	0.23	0.24	0.16	0.23	0.24	0.16
Panel B: Target characteristics	Target			Potential target		
	Mean	SD	Median	Mean	SD	Median
Firm size	6.37	2.41	6.11	6.24	2.17	6.05
Investment bank prestige	0.87	0.80	1.00	0.93	0.81	1.00
ROA (%)	5.72	19.17	10.33	7.66	17.58	11.04
Cash (%)	19.29	22.85	8.60	20.57	24.11	9.32
Leverage (%)	21.61	21.55	18.09	20.73	21.61	15.81
M/B	3.74	19.77	2.22	3.66	12.20	2.43
Diversification	0.29	0.44	0.00	0.26	0.40	0.00
Panel C: Dyad characteristics	Acquirer-target pair			Potential acquirer-target pair		
	Mean	SD	Median	Mean	SD	Median
Geographic overlap	2.57	3.41	1.00	2.18	2.96	1.00
Geographic distance	0.41	0.49	0.00	0.52	0.50	1.00
Product dissimilarity	-0.03	0.05	0.00	-0.01	0.02	0.00
3-digit SIC industry	0.45	0.50	0.00	0.27	0.44	0.00

Table 3. Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Acquirer-target pairing	1.00										
(2)	Geographic overlap	0.05	1.00									
(3)	Geographic distance	-0.07	-0.11	1.00								
(4)	Product dissimilarity	-0.27	-0.20	0.11	1.00							
(5)	3-digit SIC industry	0.14	0.03	-0.02	-0.33	1.00						
(6)	Acquirer geographic dispersion	0.00	0.45	-0.06	-0.05	-0.04	1.00					
(7)	Acquirer firm size	0.02	0.17	-0.06	-0.02	0.01	0.25	1.00				
(8)	Acquirer investment bank prestige	-0.01	-0.01	0.01	-0.07	0.11	-0.05	0.18	1.00			
(9)	Acquirer ROA	0.01	0.02	-0.05	0.01	-0.06	0.02	0.25	0.00	1.00		
(10)	Acquirer leverage	0.01	0.22	-0.06	-0.07	-0.05	0.23	0.17	-0.07	-0.01	1.00	
(11)	Acquirer cash	-0.01	-0.18	0.12	-0.04	0.16	-0.25	-0.30	0.13	-0.30	-0.40	1.00
(12)	Acquirer M/B	-0.01	-0.06	0.03	-0.01	0.07	-0.06	-0.01	0.06	0.02	-0.06	0.18
(13)	Acquirer diversification	0.01	0.04	-0.05	0.09	-0.11	0.13	0.37	-0.06	0.07	0.07	-0.28
(14)	Acquirer prior acquisition experience	0.04	0.06	-0.03	-0.02	0.01	0.05	0.32	0.03	0.09	0.00	-0.08
(15)	Acquirer internationalization	0.00	-0.20	0.06	0.10	0.04	-0.13	0.23	0.10	0.07	-0.22	0.17
(16)	Target firm size	0.01	0.25	-0.11	0.00	-0.11	0.12	0.17	-0.05	0.02	0.18	-0.18
(17)	Target investment bank prestige	-0.02	-0.01	-0.01	-0.06	0.12	0.01	0.16	0.14	0.00	0.00	0.01
(18)	Target ROA	-0.01	0.11	-0.09	0.03	-0.09	0.05	0.05	-0.03	0.13	0.10	-0.14
(19)	Target leverage	0.01	0.25	-0.08	-0.09	-0.08	0.17	0.12	-0.07	0.02	0.23	-0.20
(20)	Target cash	-0.01	-0.20	0.11	-0.02	0.19	-0.12	-0.03	0.10	-0.07	-0.20	0.25
(21)	Target M/B	0.00	-0.02	0.00	0.01	0.01	-0.01	-0.01	0.00	0.02	-0.01	0.02
(22)	Target diversification	0.01	0.08	-0.06	0.07	-0.17	0.05	0.04	-0.05	0.00	0.08	-0.10

Table 3. Correlation matrix (continue)

		(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(12)	Acquirer M/B	1.00										
(13)	Acquirer diversification	-0.06	1.00									
(14)	Acquirer prior acquisition experience	-0.01	0.11	1.00								
(15)	Acquirer internationalization	0.03	0.11	0.07	1.00							
(16)	Target firm size	-0.06	0.08	0.01	-0.10	1.00						
(17)	Target investment bank prestige	0.04	0.04	0.07	0.10	-0.06	1.00					
(18)	Target ROA	-0.02	0.04	-0.01	-0.06	0.39	-0.04	1.00				
(19)	Target leverage	-0.07	0.06	-0.03	-0.20	0.28	-0.05	0.09	1.00			
(20)	Target cash	0.08	-0.05	0.04	0.21	-0.42	0.18	-0.46	-0.41	1.00		
(21)	Target M/B	0.02	0.00	-0.01	0.03	0.00	-0.02	0.00	0.02	0.10	1.00	
(22)	Target diversification	-0.06	0.05	-0.01	-0.03	0.45	-0.15	0.18	0.13	-0.33	-0.01	1.00

Table 4. The relationship between geographic overlap and acquisition pairing and moderating effects (a conditional logit model)

DV: Acquisition pairing	(1) Baseline model	(2) H1	(3) H2	(4) H3	(5) H4	(6) H5	(7) Full model
Geographic overlap		**0.040**	**0.205**	**0.143**	**0.015**	**0.064**	**0.259**
		(0.015)	**(0.059)**	**(0.042)**	**(0.018)**	**(0.016)**	**(0.069)**
Geographic overlap × Acquirer firm size			**-0.021**				**-0.019**
			(0.007)				**(0.008)**
Geographic overlap × Acquirer geographic dispersion				**-0.113**			**-0.078**
				(0.043)			**(0.043)**
Geographic overlap × Geographic distance					**0.063**		**0.046**
					(0.021)		**(0.021)**
Geographic overlap × Product dissimilarity						**1.090**	**0.917**
						(0.244)	**(0.253)**
Geographic dispersion		-0.221	-0.245	-0.071	-0.215	-0.235	-0.148
		(0.095)	(0.096)	(0.111)	(0.095)	(0.095)	(0.113)
Product dissimilarity		-25.26	-25.31	-25.09	-25.32	-29.17	-28.50
		(1.347)	(1.349)	(1.347)	(1.351)	(1.663)	(1.674)
Geographic distance	-0.442	-0.335	-0.331	-0.332	-0.473	-0.337	-0.438
	(0.066)	(0.070)	(0.070)	(0.070)	(0.084)	(0.070)	(0.085)
3-digit SIC industry	1.951	1.390	1.381	1.384	1.395	1.383	1.377
	(0.109)	(0.118)	(0.118)	(0.118)	(0.118)	(0.119)	(0.119)
Acquirer characteristics							
Firm size	0.338	0.378	0.422	0.381	0.377	0.377	0.419
	(0.055)	(0.059)	(0.061)	(0.059)	(0.059)	(0.059)	(0.062)
Investment bank prestige	-0.147	-0.198	-0.198	-0.198	-0.194	-0.197	-0.195
	(0.046)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
ROA	0.300	0.216	0.167	0.222	0.210	0.212	0.162
	(0.375)	(0.403)	(0.405)	(0.404)	(0.404)	(0.406)	(0.407)
Leverage	0.160	0.277	0.284	0.285	0.278	0.266	0.276
	(0.240)	(0.260)	(0.260)	(0.260)	(0.261)	(0.260)	(0.261)
Cash	-0.030	-0.417	-0.440	-0.425	-0.423	-0.465	-0.484
	(0.250)	(0.275)	(0.276)	(0.276)	(0.276)	(0.278)	(0.279)
M/B	-0.000	0.000	0.001	0.000	0.000	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Diversification	0.067	0.194	0.182	0.200	0.181	0.191	0.178
	(0.104)	(0.109)	(0.110)	(0.109)	(0.110)	(0.109)	(0.110)
Prior acquisition experience	0.016	0.012	0.012	0.012	0.013	0.013	0.013
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Internationalization	-0.239	-0.095	-0.101	-0.105	-0.084	-0.059	-0.066
	(0.209)	(0.222)	(0.222)	(0.222)	(0.222)	(0.223)	(0.223)
Target characteristics							
Investment bank prestige	-0.080	-0.096	-0.097	-0.096	-0.095	-0.100	-0.100
	(0.046)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Firm size	0.358	0.351	0.352	0.346	0.351	0.355	0.352
	(0.064)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
ROA	-1.103	-1.091	-1.098	-1.096	-1.112	-1.098	-1.122
	(0.250)	(0.272)	(0.272)	(0.272)	(0.272)	(0.273)	(0.274)
Leverage	0.071	0.056	0.040	0.065	0.042	0.053	0.039
	(0.213)	(0.233)	(0.233)	(0.234)	(0.233)	(0.233)	(0.233)
Cash	-0.684	-0.877	-0.896	-0.877	-0.875	-0.895	-0.903
	(0.225)	(0.245)	(0.246)	(0.246)	(0.246)	(0.247)	(0.247)
M/B	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Diversification	0.105	0.166	0.156	0.169	0.169	0.166	0.162
	(0.104)	(0.108)	(0.109)	(0.109)	(0.108)	(0.109)	(0.109)
Observations	9,499	9,499	9,499	9,499	9,499	9,499	9,499
Deal FE	YES	YES	YES	YES	YES	YES	YES
R-square (%)	10.61	19.69	19.84	19.82	19.86	20.02	20.31

Note: Standard errors in parentheses

Table 5. Implied coefficients on geographic overlap by typical moderator value (based on Model 7 in Table 4)

	Implied coefficient	Odds ratio when increasing geographic overlap from 0 to 3	Percentage change in odds when increasing geographic overlap from 0 to 3
Geographic dispersion = 1; Geographic distance = 0; Product dissimilarity = 0			
Acquirer firm size = 2	0.143	1.5357	+53.57%
Acquirer firm size = 3	0.124	1.4506	+45.06%
Acquirer firm size = 5; Geographic distance = 1; Product dissimilarity = 0			
Geographic dispersion = 0	0.210	1.8776	+87.76%
Geographic dispersion = 1	0.132	1.4859	+48.59%
Acquirer firm size = 7; Geographic dispersion = 0; Product dissimilarity = -0.1			
Geographic distance = 0	0.034	1.1074	+10.74%
Geographic distance = 1	0.080	1.2712	+27.12%
Acquirer firm size = 8; Geographic dispersion = 0; Geographic distance = 1			
Product dissimilarity = -0.1	0.061	1.2008	+20.08%
Product dissimilarity = 0	0.153	1.5825	+58.25%

Table 6. Regression results for robustness checks

DV: Acquisition pairing	(1) Original model	(2) Alternative measures	(3)	(4) Five matches	(5) Five matches based on size
Geographic overlap	0.259	0.316	0.187	**0.276**	**0.283**
	(0.069)	(0.080)	(0.079)	**(0.074)**	**(0.073)**
Geographic overlap × Acquirer firm size (total assets)	-0.019		-0.018	**-0.020**	**-0.020**
	(0.008)		(0.008)	**(0.008)**	**(0.008)**
Geographic overlap × Acquirer firm size (total number of employees)		**-0.022**			
		(0.008)			
Geographic overlap × Acquirer geographic dispersion	-0.078	-0.081	-0.068	**-0.084**	**-0.083**
	(0.043)	(0.043)	(0.044)	**(0.051)**	**(0.050)**
Geographic overlap × Geographic distance (dummy)	0.046	0.047		**0.054**	**0.048**
	(0.021)	(0.021)		**(0.022)**	**(0.022)**
Geographic overlap × Geographic distance (actual length)			**0.012**		
			(0.007)		
Geographic overlap × Product dissimilarity	0.917	0.955	0.944	**0.970**	**0.932**
	(0.253)	(0.255)	(0.250)	**(0.251)**	**(0.248)**
Geographic dispersion	-0.148	-0.138	-0.158	-0.102	-0.109
	(0.113)	(0.112)	(0.114)	(0.110)	(0.109)
Product dissimilarity	-28.50	-28.42	-28.45	-28.05	-28.17
	(1.674)	(1.691)	(1.677)	(1.516)	(1.503)
Geographic distance (dummy)	-0.438	-0.430		-0.475	-0.471
	(0.085)	(0.085)		(0.084)	(0.084)
Geographic distance (actual length)			-0.171		
			(0.026)		
3-digit SIC industry	1.377	1.393	1.377	1.365	1.373
	(0.119)	(0.119)	(0.119)	(0.115)	(0.116)
Acquirer characteristics					
Firm size (total assets)	0.419		0.422	0.400	0.298
	(0.062)		(0.062)	(0.055)	(0.060)
Firm size (total number of employees)		0.243			
		(0.049)			
Investment bank prestige	-0.195	-0.169	-0.196	-0.171	-0.187
	(0.050)	(0.049)	(0.050)	(0.049)	(0.048)
ROA	0.162	0.145	0.217	0.109	-0.304
	(0.407)	(0.408)	(0.411)	(0.391)	(0.402)
Leverage	0.276	0.355	0.298	0.258	0.346
	(0.261)	(0.259)	(0.261)	(0.245)	(0.246)
Cash	-0.484	-0.109	-0.533	-0.633	-0.525
	(0.279)	(0.286)	(0.281)	(0.267)	(0.265)
M/B	0.001	-0.002	0.001	0.004	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Diversification	0.178	0.166	0.190	0.139	0.159
	(0.110)	(0.111)	(0.110)	(0.108)	(0.108)
Prior acquisition experience	0.013	0.016	0.013	0.014	0.012
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Internationalization	-0.066	0.0286	-0.129	-0.096	-0.116
	(0.223)	(0.223)	(0.226)	(0.214)	(0.212)
Target characteristics					
Investment bank prestige	-0.100	-0.112	-0.104	-0.092	-0.101
	(0.049)	(0.049)	(0.049)	(0.048)	(0.048)
Firm size	0.352	0.335	0.352	0.354	0.210
	(0.067)	(0.067)	(0.068)	(0.059)	(0.057)
ROA	-1.122	-1.123	-1.111	-0.995	-0.846
	(0.274)	(0.275)	(0.275)	(0.260)	(0.277)
Leverage	0.0392	0.0836	0.0392	-0.121	-0.0941
	(0.233)	(0.235)	(0.234)	(0.224)	(0.227)
Cash	-0.903	-0.895	-0.958	-0.914	-0.564
	(0.247)	(0.250)	(0.248)	(0.239)	(0.229)
M/B	0.001	0.001	0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Diversification	0.162	0.167	0.179	0.115	0.126
	(0.109)	(0.109)	(0.109)	(0.109)	(0.108)
Observations	9,499	9,357	9,499	13,665	13,616
Deal FE	YES	YES	YES	YES	YES
R-square (%)	20.31	19.74	20.75	18.79	17.90

Note: Standard errors in parentheses