# Network Learning Effects in Cross-border Mergers and Acquisitions

Jackie M.L. Chan* Chih-Sheng Hsieh†

November 15, 2018

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**Abstract**

In this paper, we study the impact of learning in foreign markets on firms' entry decision into new destinations. We propose local knowledge spillovers within spatial networks in third countries (i.e., prior destinations) as a channel through which firms learn about their destination of interest. In the context of cross-border mergers and acquisitions (M&A), acquirers obtain knowledge on new destinations from their third-country targets through the neighborhood learning effect. We present a heterogeneous-firm model of cross-border M&A with learning. Firms sort as acquirers, non-participants of M&A, and targets. Expected profits and the probability of entry into a destination increase with acquirers' accumulated experience abroad and the strength of signals observed from their third-country targets. Using data on global cross-border M&A activity from 1995 to 2016, we find strong empirical support for the model at both the macro and micro levels. In particular, at the micro level, we examine over 2,800 non-US acquirers that invested in the US and subsequently in non-US foreign destinations. Controlling for accumulated experience in other third countries, we find that the cross-border M&A activity (purchases and sales) of the US targets' neighbors has a positive impact on the destination choice of the non-US acquirers. Moreover, learning effects are complementary across firms' sources of information.

*JEL classification codes: F14, F21, F23, D85*
*Keywords: Cross-border mergers and acquisitions, spatial networks, knowledge spillovers, third countries, neighborhood learning.*

*We thank Yishu Wang for his research assistance, as well as Treb Allen, Eik Swee, Ben Li, and participants of seminars at Nanyang Technological University, Singapore Management University, National Singapore University Lee Kuan Yew School of Public Policy, University of Melbourne, and Deakin University for their comments. Support from Chinese University of Hong Kong Research Committee Direct Grant for Research is gratefully acknowledged. Correspondence: Jackie M.L. Chan, Department of Economics, 9/F, Esther Lee Building, Chinese University of Hong Kong, Shatin, N.T., Hong Kong, jmlchan@cuhk.edu.hk.

†Chih-Sheng Hsieh, Department of Economics, 9/F, Esther Lee Building, Chinese University of Hong Kong, Shatin, N.T., Hong Kong, cshsieh@cuhk.edu.hk.

# 1 Introduction

With the integration of world markets, firms are more connected now than ever before. Empirical evidence suggests that firms do not operate in isolation, and their decisions to export or invest abroad are influenced by the networks they belong to. In both the origin country of the firm and destination of interest, information frictions may be alleviated by knowledge spillovers from personal and business connections. For example, the cross-border transactions of domestic firms generate positive externalities within their networks for entry into international markets. Such networks may arise with the interaction of firms through spatial proximity (e.g., Fernandes and Tang, 2014; Kamal and Sundaram, 2016), buyer-supplier relationships (e.g., Bai et al., 2017), and the intra-firm movement of employees (e.g., Mion and Opromolla, 2015; Muendler and Rauch, 2018). In the destination market, social networks formed through labor migration have been shown to impact both trade and foreign direct investment (FDI) (e.g., Rauch and Trindade, 2002; Javorcik et al., 2011; Burchardi et al., 2017).

Besides the origin and destination countries, information about new markets may be obtained through other countries that have been previously served (e.g., Schmeiser, 2012; Albornoz et al., 2012; Chaney, 2014). Cross-border transactions connect firms to other participants in international markets, and in particular, multinationals that invest abroad using cross-border mergers and acquisitions (M&A) are exposed to the networks of their target companies in prior destinations. Therefore, these prior destinations, which we will refer to as "third countries," provide an additional channel for information on the new destination of interest to be gained. In this paper, the role of knowledge spillovers for cross-border M&A is examined in a multilateral setting. We propose and test the hypothesis that acquirer firms learn about new destination markets through their targets' networks in third countries. We focus on the spatial networks formed between targets and their neighboring firms, and show theoretically and empirically their impact on the destination choice of acquirers.

Our theoretical framework introduces third-country learning effects into the cross-border M&A model of Nocke and Yeaple (2007). In each period, firms of heterogeneous productivity may participate in the cross-border M&A market as acquirers or targets. The former pays a fixed cost of entry and an acquisition price to purchase the brand and production capabilities of the latter.[1] Hence, firms sort as acquirers, non-participants, and targets by productivity. Importantly, the sorting pattern is also affected by firms' expected profits in foreign markets, which depend on the acquisition match quality. Firms hold prior beliefs about the match quality, with the mean increasing in their accumulated experience in third countries. The value of this experience is weighted by the (economic or geographic) closeness of each third country to the destination of interest. Using the micro-level signals received from the spatial networks of their

[1] As in Nocke and Yeaple (2007), the productivity of acquirers is assumed to be mobile. While Nocke and Yeaple (2007) also introduce a non-mobile capability to examine the choice of entry modes between exporting, greenfield investment, and M&A, we focus on learning effects in cross-border M&A and abstract from the various entry modes of FDI. For other theories on the determination of FDI entry mode, see, for example, Helpman et al. (2004), Chen and Moore (2010), and Norbäck and Persson (2007). Alternative models of cross-border M&A with firm heterogeneity are studied in, for instance, Head and Ries (2008) and Blonigen et al. (2014).

third-country targets, acquirers learn about the destination and update their prior beliefs. In contrast to accumulated experience, the impact of these networks, which consists of neighboring acquirers to and targets of the destination of interest, varies depending on the location of the acquirer's target within the third country. The model predicts that an acquirer's probability of entry into a new destination is increasing in the bidirectional M&A activity (purchases and sales) of its target's neighbors to the destination, and in the firm's own accumulated experience in third countries. Furthermore, learning effects are complementary across the firm's sources of information, as each effect becomes more pronounced with greater knowledge on the destination obtained via the other channels.

We provide strong empirical support for the model's predictions at both the macro and micro levels. The analysis uses the universe of cross-border M&A data for 189 origin and 209 destination countries from Thomson-Reuters SDC Platinum. We study the extensive margin of M&A activity from 1995 to 2016, but utilize the full history of firms' investments abroad available starting from 1981. At the macro level, the number of bilateral acquisitions from an origin country to a destination is positively associated with the origin's aggregate experience in foreign markets, as measured by the lagged weighted sum of acquisitions across third countries. Weights reflect the closeness of each third country to the destination, and we use the inverse of geographic distance and the volume of cross-border M&A activity as proxies. The latter, which includes both acquisitions and sales, provides a measure of the economic interaction between the two countries. These results hold controlling for other determinants of cross-border investment, such as market size and bilateral distance.

At the micro level, we investigate the role of learning in third countries on the destination choice of acquirers. The third-country neighborhood learning effect and the impact of accumulated experience are examined both individually and jointly. Given the comprehensive information available on firm locations in the US, we study the neighborhood learning effect associated with the spatial networks in this third country. However, the full global M&A data is used to measure firms' aggregate experience overseas. Hence, our sample consists of over 2,800 non-US acquirers from 54 countries that invested at least once in the US, and subsequently, purchased one or more non-US targets. We geocode the locations of US firms, and use a radius of 100km to define the neighborhoods of acquirers' US targets. The regression results show a positive impact of the (lagged) cross-border M&A activity of the US targets' neighboring firms on the destination choice of non-US acquirers. This effect is observed in both directions for neighboring acquisitions and target sales, and suggests that knowledge spillovers from third-country targets are transferred to acquirers in the origin. Thus, there is knowledge diffusion both within the country and across countries through the ownership structure of multinationals. Using a comprehensive set of controls, including destination-year, origin-year, and firm-year fixed effects, we demonstrate that these results are not driven by other demand- and supply-side shocks to cross-border investment. In addition, our regressions account for the potential endogenous choice of US target location by controlling for the cross-border M&A activity of the same neighborhood in the year before the acquirer's entry into the US. The results are also robust to an instrumental variable strategy, where the interaction between the origin and destination's historical migrant population in the US at the county level is used as the instrument.

The third-country neighborhood learning effect is found to be stronger for neighboring firms in the same state, same sector, and downstream (as opposed to upstream) sectors. Furthermore, we construct the cross-border M&A network as a two-mode (bipartite) network, and use eigenvector centrality to capture both the number and quality of links between US neighboring firms and destinations (Faust, 1997; Borgatti and Everett, 1997). For example, acquirers that are more central in the global M&A network invest not only in a larger number of destinations, but the destinations themselves also have more links to firms. Thus, we construct a measure of firms' information on international markets based on their observed investment patterns. We find that the learning effect is increasing in the network centrality of neighboring firms, and can largely be explained by the presence of experienced and well-connected acquirers and targets within the US target's spatial network.

We also show that accumulated experience, measured by the firm-level weighted sum of acquisitions to third countries, is an important determinant of acquirers' destination choice. While the source of knowledge spillovers in these non-US third countries cannot be identified, prior entry into countries that are closer and more integrated with the destination of interest is associated with a higher probability of acquisition. Importantly, the neighborhood learning effect remains even after controlling for this additional learning channel. Consistent with the model's predictions, the neighborhood learning effects of both directions are complementary, and more pronounced when firms have greater experience overseas and more target locations in the US. Therefore, the value of third-country knowledge spillovers to multinationals increases with both entry into more third countries, as well as more locations within a third country.

## 1.1 Literature review

Our findings contribute to a literature that seeks to understand how firms learn about foreign markets in cross-border transactions. In particular, recent research has emphasized the role of networks for knowledge diffusion in international trade. For instance, empirical evidence from both firm- and transaction-level data suggests that exporters' choice of destination market, volume of sales, and even identities of their trade partners are affected by the information gained through their geographic neighbors (e.g., Koenig et al., 2010; Fernandes and Tang, 2014; Kamal and Sundaram, 2016; Cassey et al., 2016). However, to the best of our knowledge, this is the first paper to study the knowledge spillovers of micro-level spatial networks in the context of FDI.[2] Moreover, whereas the impact of exporters or importers are generally examined in isolation due to data constraints, we analyze the spillovers from both directions (i.e., purchases by acquirers and sales of targets) in the same empirical framework using our global cross-border M&A

[2]Importers also receive and benefit from the information of their geographic neighbors (e.g., Bisztray et al., 2017; Hu and Tan, 2017). Meanwhile, Cai et al. (2015) show that target firms located in urban areas are more likely to receive a takeover bid and be purchased compared to firms in rural areas. Our findings suggest that stronger knowledge spillovers among urban firms that are more clustered may be a potential explanation for their results.

transaction-level data, and compare the two channels both qualitatively and quantitatively.

Besides spatial networks, knowledge on markets abroad can be gained through other external sources. A related strand of literature in finance studies social ties between companies and M&A outcomes. For instance, board members of different companies may be connected through their past education or employment (Cai and Sevilir, 2012; Ishii and Xuan, 2014; Renneboog and Zhao, 2014). Personal connections created from the firm-to-firm movement of employees and managers also facilitate the transfer of destination-specific knowledge between companies (e.g., Mion and Opromolla, 2015; Mion et al., 2017; Muendler and Rauch, 2018). Similarly, information frictions of trade and FDI are alleviated by the networks formed through cross-border ethnic ties and migration (e.g., Rauch and Trindade, 2002; Parsons and Vézina, 2018; Javorcik et al., 2011; Burchardi et al., 2017; Chan and Zheng, 2018).

Learning also occurs with sales and operations in international markets. In particular, the correlation of profits across destinations implies a pattern of sequential entry into foreign markets based on firms' history of cross-border transactions (e.g., Albornoz et al., 2012).[3] Schmeiser (2012) explains this export pattern by modeling learning as a decline in entry costs, and numerically demonstrates firms' initial entry into a subset of profitable destinations, followed by a gradual transition towards more distant markets.[4] Furthermore, the economic integration of foreign countries may also facilitate firms' entry into subsequent destinations. For example, Chaney (2014) proposes a model where the network of contacts established in foreign markets reduces search frictions and allows firms to search remotely for trade partners in new destinations.[5] These networks may be formed by trade relationships between exporters and importers, as He and Lugovskyy (2018) document recently using a subset of matched Colombian exporters and Chilean firms.

This paper makes theoretical and empirical contributions to the literature with a detailed analysis of learning effects in third countries. First, we demonstrate the role of firms' history in the cross-border M&A market for their choice of destination.[6] Second, we provide a micro-foundation for the transmission of information from third-country networks to firms in the origin through the direct ownership link between targets and acquirers. Using comprehensive transaction-level data on cross-border M&A, we analyze these two effects both separately and jointly to understand how firms aggregate information from different sources of knowledge. In addition, we find substantial heterogeneity within the networks with respect to geography, industrial linkages, and the centrality of firms.

Our results have important implications for the sequential entry of acquirers into foreign

[3] Nguyen (2012) presents a similar model where firms forecast profits in other destinations upon entering a foreign market. Separately, learning may result in dynamic outcomes such as improvements in productivity or adaption to foreign market demand shocks (e.g., De Loecker, 2007; Berman et al., 2018).

[4] For additional empirical evidence of sequential exporting, see for example, Freund and Pierola (2010), Berthou and Ehrhart (2017), and Sheard (2014).

[5] A related literature examines the role of trade intermediaries in overcoming trade frictions. These intermediaries are not only restricted to the origin or destination countries, but may be located in foreign countries (e.g., Antràs and Costinot, 2010; Chan, 2018).

[6] Blonigen et al. (2007) study the impact of spatial networks on FDI at the aggregate level. Using a modified gravity model, they show that US outbound FDI is influenced by spatial lags as well as surrounding-market potential.

markets. Traditional gravity forces predict a hierarchy or pecking order of destinations for firms, in which, for example, countries that are closer to the home market are more attractive (e.g., Chan and Manova, 2015). However, Eaton et al. (2011) find significant deviations from such a hierarchy for French exporters. The order in which firms enter foreign markets may also be predicted by "extended gravity" forces, as exporters are more inclined to sell in destinations that are similar to their previous export markets (Morales et al., 2017; Defever et al., 2015). Likewise, Egger et al. (2014) show similar patterns for the establishment of foreign affiliates. Consistent with this prior literature, we find that acquirers are indeed more likely to invest in countries that are similar to their previous destinations. However, we also show how multinationals may deviate from this hierarchy of destinations predicted by extended gravity forces. In particular, deviations will be observed when acquirers receive strong positive signals about other markets from their third-country targets.

The rest of paper is organized as follows. In Section 2, we present the theoretical model and derive the aggregate and firm-level implications. Section 3 describes the data, while Section 4 discusses the empirical framework. Section 5 presents the macro- and micro-level empirical results. Lastly, Section 6 concludes.

# 2 Theoretical model

We build a theoretical model of cross-border M&A to study the impact of learning on firms' foreign acquisitions. In each period, firms in the origin country decide whether to become an acquirer in the cross-border M&A market, and if so, which destination countries to enter. We refer to a prior destination of the acquirer as a third country. Knowledge is accumulated in this third country, enabling the multinational firm to learn about its new destination of interest.

## 2.1 Demand

The world consists of $N$ countries, indexed by $m$ for the origin, $n$ for the destination of interest, and $r$ for a third country (i.e., prior destination). Each country $n$ has a mass $L_n$ of identical agents sharing aggregate income $Y_n$. Preferences are defined by:

$$U_n = \left( \int_{\omega \in \Omega_n} \left( e^{-\mu_n(\omega)} \right)^{\frac{1}{\sigma}} q_n(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}.$$

Because consumers are identical, we may denote $q_n(\omega)$ as the aggregate consumption of variety $\omega$ in the set of varieties $\Omega_n$ in country $n$, with $\sigma > 1$ as the elasticity of substitution across varieties. The term $e^{-\mu_n(\omega)}$ serves to shift the variety-specific demand of a firm, and accordingly, its profits. Solving the consumer's maximization problem, the aggregate demand for variety $\omega$ is:

$$q_n(\omega) = e^{\mu_n(\omega)} p_n(\omega)^{-\sigma} Y_n P_n^{\sigma-1}, \tag{1}$$

where $P_n = \left( \int_{\omega \in \Omega_n} p_n(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$ is the ideal price index.

Each country $n$ has $G$ cities, indexed by $g$. Each city is populated by consumers $L_{ng} \in (0, L_n)$ as determined by the demand for labor from firms, with $\sum_{g=1}^{G} L_{ng} = L_n$. With competitive markets, wages $c$ are equalized across cities within a country, i.e., $c_{ng} = c_n$, $\forall c$. Migration across cities within a country is assumed to be costless, while migration across countries is prohibited.[7]

## 2.2 Firms and production

On the supply side, each city $g$ in country $m$ has a mass $K_m^g$ of risk neutral firms, indexed by $i$ (and later by $j$ for $i$'s neighbors). Firms produce only in the city where they are located, but sales are made to the entire domestic market, and goods are distributed across cities within a country at zero cost. We restrict our attention to cross-border M&A, and assume no trade across international borders, nor domestic M&A. Prior to production, firms decide whether or not to participate in the cross-border M&A market. As a participant, the firm must choose to be either an acquirer (i.e., buyer) or a target (i.e., seller). We first describe the production process, then move backwards to discuss the cross-border M&A market.

Each firm produces a unique variety, and is endowed with productivity $\varphi > 0$ drawn from the distribution $F(\varphi)$. An unacquired firm produces for the domestic market given its productivity, maximizing its profits subject to Eq. (1). As in the standard Melitz (2003) model, for firm $i$ in country $m$, the optimal price is a constant markup over marginal costs, $p_{im}(\varphi) = \frac{\sigma}{\sigma-1}\frac{c_m}{\varphi}$. For simplicity, we assume that local sales do not require fixed costs, and are made with $\mu_m(\varphi) = 0$, $\forall \varphi$.[8] Thus, domestic profits are:

$$\pi_{im}(\varphi) = S_m \varphi^{\sigma-1}, \tag{2}$$

where $S_m \equiv \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}c_m\right)^{1-\sigma} Y_m P_m^{\sigma-1}$.

Next, consider an acquirer with productivity $\varphi$ in country $m$ that has bought a target firm with productivity $\varphi'$ in country $n$ for the price $V_n(\varphi')$. Assume that the acquirer replaces the brand of the target with its own upon purchase, and that this relationship endures for one period.[9] This implies that in each period, firms have no incentive to purchase more than one target in a destination.[10] As in Nocke and Yeaple (2007), the acquirer's productivity is "mobile" and transferred to the target during the cross-border M&A transaction. Thus, in destination $n$, the acquired target only uses the highest productivity available between itself ($\varphi'$) and the acquirer from country $m$ ($\varphi$), with $\varphi > \varphi'$ assumed. In other words, all acquired target firms

[7] The majority of our theoretical results follows even without introducing multiple cities within a country. In our estimation sample with the US as the third country, 49% of foreign acquirers have purchased targets in more than one location in the US over the sample period. The average number of locations is 2.80, and the average amongst firms that have more than one location is 4.69. Because the share of acquirers with multiple locations is non-trivial, we introduce multiple locations in the general setup of the model.

[8] The main results of the model would not change with fixed costs for domestic production. Assuming that fixed costs of domestic production are lower than those for cross-border M&A, the least productive firms would not be able to cover the costs to produce for the local market, and would instead choose to sell itself in the cross-border M&A market. This is almost identical to the implications of the model below.

[9] Firms are assumed to make myopic decisions in this model, and are only concerned with expected profits in the upcoming period. Thus, we abstract from analyzing the dynamic stream of profits and its impact on the acquisition price.

[10] Roughly 11% of firm-destination pairs in the entire sample, as well as the estimation sample, involve multiple transactions in a year.

produce with the productivity of their parent company. Profits of firm $i$ from purchasing a target with productivity $\varphi'$ in destination $n$ are:

$$\pi_{imn}(\varphi, \varphi') = e^{\mu_{imn}(\varphi)} S_n \varphi^{\sigma-1} - F_{mn} - V_n(\varphi'). \tag{3}$$

In addition to the acquisition price, the firm incurs the fixed cost of investing abroad, $F_{mn}$. Moreover, in the context of M&A, $e^{\mu_{imn}(\varphi)}$ may be thought of as the match quality between the acquirer and target, which improves synergy and profits. Information about the destination increases the match quality. In particular, this knowledge is obtained through the entry of third countries.

### 2.3 Cross-border M&A and sorting

Cross-border M&A transactions are made before any production occurs. Firms decide whether or not to be a participant of the perfectively competitive cross-border M&A market, and if so, whether to be an acquirer or target. Because the target produces with the acquirer's productivity $\varphi$ instead of its own productivity $\varphi'$, any target is equally valuable to the acquirer. Therefore, the acquisition price in destination $n$ for all $\varphi'$ may be denoted as $V_n(0)$. Firms that participate as targets in the cross-border M&A market are pooled within their country, and the acquirer is randomly matched to one of these (ex-post) identical targets. In particular, the acquirer cannot choose the city in which the target is located.

Although a firm will not make more than one acquisition within a country in any given period, it may invest in multiple foreign destinations. In particular, we define

$$\mu_{imn}(\varphi) = \alpha \varepsilon_{imn} + (1-\alpha) D_{imn}(\varphi), \text{ where } D_{imn}(\varphi) = \sum_{r=1}^{N} W_{rn} \mathbf{1}[\widehat{acquirer}]_{imr}(\varphi). \tag{4}$$

This is a weighted average of an idiosyncractic component, $\varepsilon_{imn}$, and a term capturing the firm's accumulated experience and knowledge in third countries, $D_{imn}(\varphi)$.[11] The former is a random variable normally distributed with mean 0 and variance $\nu$ (i.e., $\varepsilon_{imn} \sim N(0, \nu)$), revealed to the firm only after its investment decision is made. We use hat notation to denote the past, and $\mathbf{1}[\widehat{acquirer}]_{imr}(\varphi) \in \{0, 1\}$ indicates whether the firm made an acquisition in third country $r$ previously. For each country that contributes to the total experience of the firm, we use $W_{rn}$ to weight the closeness of third country $r$ to destination $n$. Empirically, we construct the weights based on geographic distance and measures of economic interaction such as the volume of cross-border M&A activity. $D_{imn}$ may be interpreted as a "macro-level" signal that the firm receives about destination $n$ based on its accumulated experience and knowledge in third countries. Therefore, given the normal distribution of $\varepsilon_{imn}$, expected profits are:

$$E[\pi_{imn}(\varphi, \varphi')] = e^{\frac{\alpha^2 \nu}{2} + (1-\alpha) D_{imn}(\varphi)} S_n \varphi^{\sigma-1} - F_{mn} - V_n(0). \tag{5}$$

[11]The weights may be chosen arbitrarily and do not affect the theoretical result below, i.e., Proposition 1. This particular form of weights is chosen to draw a parallel with the weighted average of signals in Eq. (10) below.

We can now characterize and sort firms as acquirers, targets, and non-participants of the cross-border M&A market. For the least productive firms, they find the acquisition price $V_m(0)$ to be larger than domestic profits $\pi_{im}$, and become targets for sale. While firms with intermediate levels of productivity prefer domestic profits to the acquisition price, they are unable to overcome the costs of acquisition in $n$, and will choose to be non-participants of the cross-border M&A market in $n$. Lastly, the most productive firms expect positive profits in market $n$, and will choose to buy a target in $n$ as an acquirer. They also invest in more destinations, further amplifying their profits. This implies that there are two cutoff productivities in determining the sorting pattern. The first cutoff determines the firm's decision to become a target. It depends on the market characteristics of the firm's origin country $m$, but is independent of destination $n$. We denote this cutoff as

$$\underline{\varphi}_m \equiv \left(\frac{V_m(0)}{S_m}\right)^{\frac{1}{\sigma-1}}. \tag{6}$$

The second cutoff pins down the set of firms that invest in a given destination $n$. Specifically, the expected profits of an acquisition in $n$ are positive when productivity is greater than

$$\overline{\varphi}_{mn} \equiv \left(\frac{F_{mn} + V_n(0)}{S_n e^{\frac{\alpha^2 \nu}{2}}}\right)^{\frac{1}{\sigma-1}}. \tag{7}$$

Note that because shocks $\varepsilon_{imn}$ are only revealed ex-post, the choice to make a purchase in $n$ is determined only by the initial draw of productivity $\varphi$, and not by the (past) realizations of the shocks themselves.

The sorting pattern is displayed in Figure 1. The dotted line shows domestic profits $\pi_{im}$, while the dashed line plots profits for an acquisition in destination $n$ if they are not affected by past experience (i.e., $\mu_{imn}(\varphi) = 0$). The solid line instead includes the influence of accumulated experience on expected profits through $\mu_{imn}$. Firms with productivity less than $\underline{\varphi}_m$ find it more profitable to be acquired for the price of $V_m(0)$ than to earn profits domestically, and choose to become targets. To the right of $\underline{\varphi}_m$, only more productive firms with strong experience abroad are able to overcome the cost of foreign acquisition, i.e., $\varphi > \overline{\varphi}_{mn}$, and make a purchase in $n$. Thus, we have three mutually exclusive sets of firms with respect to destination $n$:

$$\begin{aligned}
&\text{Set of target firms} = \{\varphi : \varphi < \underline{\varphi}_m\} \\
&\text{Set of non-participants in } n = \{\varphi : \underline{\varphi}_m \leq \varphi < \overline{\varphi}_{mn}\} \\
&\text{Set of acquirer firms in } n = \{\varphi : \overline{\varphi}_{mn} \leq \varphi\}.
\end{aligned}$$

Note that three sets of firms may also be defined across all destinations, where the productivity of non-participants is less than $\overline{\varphi}_{mn}$ for all $n$, and acquirers have productivity above $\overline{\varphi}_{mn}$ for any $n$.

Denote $A_{mn}$ as the aggregate number of acquisitions from origin $m$ to destination $n$. For now, acquirers in different cities within an origin country are identical if they have the same

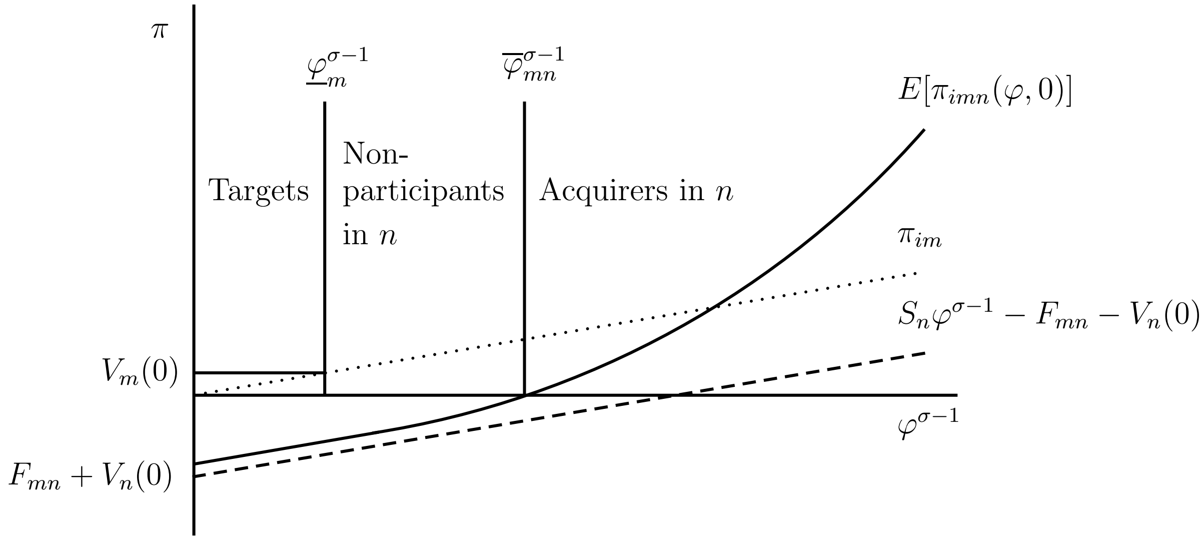



Figure 1: This figure shows domestic profits in $m$ and profits in foreign market $n$ through M&A. Countries $m$ and $n$ are drawn with the same market size. Firms sort as targets, non-participants in $n$, and acquirers in $n$.

productivity draw. Thus, we can simply sum across all cities within the country and obtain:

$$A_{mn} = \sum_{g=1}^{G} K_m^g \left[1 - F(\overline{\varphi}_{mn})\right]. \tag{8}$$

Now, suppose that $D_{imn}(\varphi)$ increases for an individual firm. From Figure 1, we can see that the set of acquirer firms must be non-decreasing in the past experience of all firms that are not targets. In particular, if $D_{imn}(\varphi)$ increases for all firms with productivity above $\underline{\varphi}_m$, $\overline{\varphi}_{mn}$ must decrease, and some non-participants will switch to become acquirers for destination $n$. Thus, we have Proposition 1:

**Proposition 1.** *The aggregate number of acquisitions from country $m$ to $n$, $A_{mn}$, is non-decreasing in the number of third countries $r$ previously entered and their closeness to $n$.*

## 2.4 Neighborhood learning effects

To examine the learning mechanism in greater detail at the micro level, we now provide a heterogeneous source of variation for the random signal $\varepsilon_{imn}$. Firms continue to face uncertainty about $\mu_{imn}(\varphi)$, but their beliefs are partially based on their experience in third countries. We follow the literature in applying the DeGroot (2004) linear updating model (e.g., Fernandes and Tang, 2014; Timoshenko, 2015; Berman et al., 2018). Thus, assume that firms hold a prior belief that $\mu_{imn}(\varphi)$ is normally distributed with mean $D_{imn}(\varphi)$ and variance $v_1$ (i.e., $\mu_{imn}(\varphi) \sim N(D_{imn}(\varphi), v_1)$). That is, the macro-level signal observed from accumulated experience overseas establishes the mean of the prior distribution. Firms update their prior belief from the micro-level signals observed in third countries. Because we focus on the entry choice

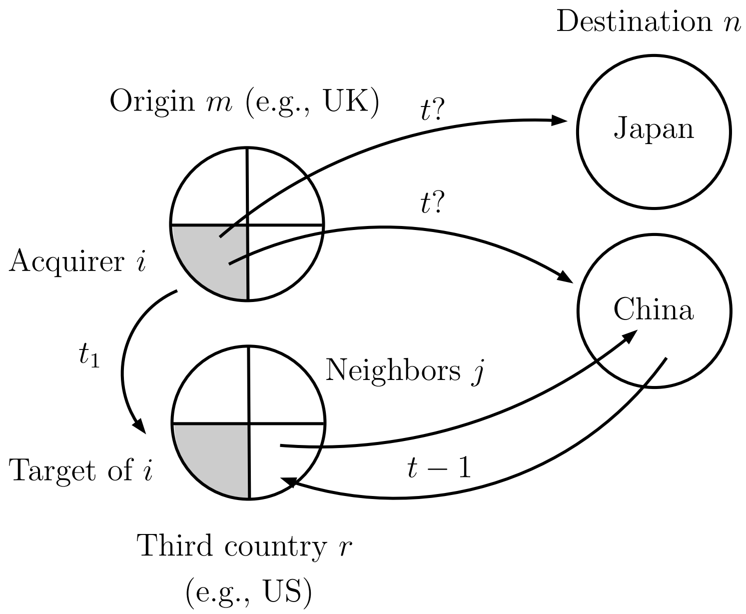



Figure 2: Schematic diagram of entry into a third country and destination of interest.

to new destinations empirically, we further assume that firms do not update their beliefs about a market from the realizations of $\mu_{imn}(\varphi)$.[12]

Each of the acquirer's targets in the third countries obtain knowledge spillovers from a neighborhood learning effect. As part of the spatial network of cross-border M&A, the target in third country $r$ is exposed to localized knowledge spillovers from either acquirers to or targets of destination $n$. While the acquirer-target ownership link only lasts for one period, we assume that the acquirer maintains a connection to the target, and this knowledge diffusion, of both directions, is transferred to the acquirer.[13] Therefore, the neighborhood learning effect is specific to the location of the acquirer's target in the third country. In contrast, the externalities of the macro-level signal are common across foreign acquirers that invest in the same third country, regardless of their target's location. The scenario is depicted in Figure 2, where a shaded region indicates a firm in one city. Acquirer $i$ in origin $m$ (e.g., the United Kingdom) has purchased a target in third country $r$ (e.g., the US) at a certain time $t_1$. At the current time $t$, it chooses amongst the set of destinations $n$, such as Japan and China. Suppose at time $t-1$, the neighbors of $i$'s target purchase and/or sell to some firm in China. Then, acquirer $i$ learns about China through its target in $r$, and this has a positive impact on its choice of destination at time $t$.

Thus, for each city $g$ in third country $r$ that acquirer $i$ invested in previously, the acquirer receives two signals from the cross-border M&A activity observed through their target, one from the neighboring acquirers and the other from the neighboring targets. Due to the random assignment of foreign entrants to a destination's cities, acquirers in a third country with the same productivity are no longer identical if their targets are located in different cities. Cities will

[12]This assumption is generally supported by our empirical study. In the full data sample, 83.5% of firm-destination pairs are new entries into the destination by firms, while the remaining 16.5% are re-entries.

[13]Because we do not observe the sale of ownership stake in the US target by the non-US acquirer, the same implicit assumption is made for the empirical analysis.

generally differ by the cross-border activity of their firms, and the composition of neighbors for the acquirers' targets will also vary. Therefore, the productivity of acquirers from origin $m$ and the micro-level signals obtained from the neighborhood learning effects in $r$ are uncorrelated, and we cannot use $\overline{\varphi}_{rn}$ to denote the cutoff productivity above which all firms in $r$ will be acquirers to $n$. The signals obtained from neighboring acquirers and targets are, respectively:

$$d^g_{imrn} = \sum_{h=1}^{G} K^h_r \left[ \int_{\underline{\varphi}_r}^{\infty} w_{ijr} \mathbf{1}[\widehat{acquirer}]_{jrn}(\varphi) dF(\varphi) \right], \tag{9a}$$

$$\delta^g_{imrn} = \sum_{h=1}^{G} K^h_r \left[ \int_{0}^{\underline{\varphi}_r} w_{ijr} \mathbf{1}[\widehat{target}]_{jrn}(\varphi) dF(\varphi) \right]. \tag{9b}$$

The indicator variable $\mathbf{1}[\widehat{target}]_{jrn}(\varphi)$ is equal to 1 if firm $j$ in country $r$ is a target of an acquisition from $n$, and zero otherwise. A neighboring firm may operate in the same city as $i$'s target, or in another city $h$. Moreover, in the equations above, each neighboring firm $j$ in city $h$ is weighted by $w_{ijr}$, an element of the updating matrix $\mathbf{w}_r$. The importance of $j$ to $i$'s target may be a function of, for instance, the geographic distance between city $h$ of firm $j$ and city $g$ of $i$'s target.

Both signals are assumed to be drawn from the normal distribution with mean $\mu'_{imn}(\varphi)$ and variance $v_2$. Define $G^A_{imr}$ as the number of cities in $r$ that had a target purchased by the acquirer. In the empirical analysis, we are restricted to the study of US as the third country. Therefore, for simplicity, we do not concern ourselves with how micro-level signals from different third countries are aggregated. However, by adding up the signals within the US, we define the total signals received as $d_{imrn} = \sum_{g=1}^{G^A_{imr}} d^g_{imrn}$ and $\delta_{imrn} = \sum_{g=1}^{G^A_{imr}} \delta^g_{imrn}$. Then, by DeGroot (2004), the posterior distribution of $\mu_{imn}(\varphi)$ is normally distributed with mean:

$$\mu'_{imn}(\varphi) = \frac{a}{G^A_{imr}} \Big( d_{imrn} + \delta_{imrn} \Big) + (1-a) D_{imn}(\varphi), \tag{10}$$

where $a = \frac{2G^A_{imr}}{v_2} \left( \frac{1}{v_1} + \frac{2G^A_{imr}}{v_2} \right)^{-1}$, and the variance is $v' = \left( \frac{1}{v_1} + \frac{2G^A_{imr}}{v_2} \right)^{-1}$. Thus, the mean of the posterior distribution is essentially a weighted average of the micro-level signals from the neighborhood learning effect, and the macro-level signal of accumulated experience in third countries. Expected profits are:

$$E[\pi_{imn}(\varphi, \varphi')] = e^{\mu'_{imn}(\varphi) + \frac{v'}{2}} S_n \varphi^{\sigma-1} - F_{mn} - V_n(0). \tag{11}$$

The timing is as follows. At the start of each period, firms choose whether or not to participate in the cross-border M&A market, either as an acquirer or target, based on $\mu'_{imn}$ observed from last period's cross-border M&A activity. The acquisition price $V_n(0)$ at each destination must adjust such that the cross-border M&A market clears in all countries. Next, all acquirers in a destination are (randomly) matched to a target, and production takes place. At the end of each period, firms that invested in a new destination $r$ update the mean of their prior beliefs $D_{imn}(\varphi)$ for each destination $n$. Meanwhile, all firms that invested abroad observe the micro-level signals to update their beliefs about $n$ for the next period.

Firms are assumed to make myopically optimal entry decisions into destinations that maximize profits in the current period, without considering their effect on future profits in either the same or different destinations (Golub and Sadler, 2016). As before, in partial equilibrium, an increase in expected profits can only serve to raise the probability that the firm will invest abroad. Thus, both micro-level signals have a positive impact on the firm's destination choice:

**Proposition 2.** *The probability of acquisition in destination $n$ is increasing in the strength of micro-level signals from neighboring acquirers, $d_{imrn}$, and targets, $\delta_{imrn}$, of the third country targets* $\left(\frac{\partial E(\pi_{imn})}{\partial d_{imrn}} > 0, \text{ and } \frac{\partial E(\pi_{imn})}{\partial \delta_{imrn}} > 0\right)$.

In addition, the information obtained from neighboring acquirers and targets have complementary effects on the entry decision:

**Proposition 3.** *The impact of the micro-level signals $d_{imrn}$ and $\delta_{imrn}$ on the probability of acquisition in destination $n$ is stronger when the other micro-level signal is large* $\left(\frac{\partial^2 E(\pi_{imn})}{\partial d_{imrn}\partial \delta_{imrn}} > 0\right)$.

Next, we examine the role of $G^A_{imr}$, i.e., the number of cities in third country $r$, for the neighborhood learning effect. Because this variable is not destination specific, it would have a similar qualitative effect across all destination countries. Nevertheless, the number of locations influences the weight placed on the micro- versus macro-level signals in the updating process, and therefore, the marginal effect of the micro-level signals themselves.

**Proposition 4.** *If $1 + a(d_{imrn} + \delta_{imrn} - D_{imn}) > 0$, the impact of the micro-level signals $d_{imrn}$ and $\delta_{imrn}$ on the probability of acquisition in destination $n$ is stronger with more locations in the third country* $\left(\frac{\partial^2 E(\pi_{imn})}{\partial d_{imrn}\partial G^A_{imr}} > 0, \text{ and } \frac{\partial^2 E(\pi_{imn})}{\partial \delta_{imrn}\partial G^A_{imr}} > 0\right)$.

The cross-partial derivative of expected profits with respect to $d_{imrn}$ (or $\delta_{imrn}$) and $G^A_{imr}$ (i.e., $\frac{\partial^2 E(\pi_{imn})}{\partial d_{imrn}\partial G^A_{imr}}$) is proportional to $1 + a(d_{imrn} + \delta_{imrn} - D_{imn})$. The weight placed on the micro-level signals, $a$, is increasing in the number of cities, so the marginal effect of the micro-level signals increases as well. There is also a secondary effect on the level of expected profits. If the firm updates positively with $d_{imrn} + \delta_{imrn} > D_{imn}$, then a larger weight on the micro-level signals is associated with greater expected profits. On the other hand, if $d_{imrn} + \delta_{imrn} < D_{imn}$, then a smaller weight on the micro-level signals is preferred. In this case, a sufficiently small weight $a$ mitigates the second effect and can still guarantee that the cross-partial derivative is positive.

Experience in third countries that are closer or more similar to the destination of interest increases the probability of entry. Furthermore, the model predicts that the neighborhood learning effects are complementary to accumulated experience, in which information from one source is reinforced by the other:

**Proposition 5.** *The probability of acquisition in destination $n$ is increasing in accumulated experience in third countries $r$ weighted by their closeness to $n$, $D_{imn}$, especially when the micro-level signals, $d_{imrn}$ and $\delta_{imrn}$, are large* $\left(\frac{\partial E(\pi_{imn})}{\partial D_{imn}} > 0, \frac{\partial^2 E(\pi_{imn})}{\partial D_{imn}\partial d_{imrn}} > 0 \text{ and } \frac{\partial^2 E(\pi_{imn})}{\partial D_{imn}\partial \delta_{imrn}} > 0\right)$.

It should be noted that we have chosen to model learning as generating greater revenue, as opposed to a reduction in (fixed) costs. The latter approach is taken by, for instance, Schmeiser (2012). While this alternative modeling assumption would deliver the same predictions with regards to the levels of either the micro- or macro-level signals, it would also give the opposite prediction for the interaction effects (i.e., Proposition 3 and the latter part of Proposition 5). That is, all three signals would act as substitutes instead of complements. As Section 5 below demonstrates, we are motivated by the empirical evidence to model the effect of learning on revenues instead of costs.

# 3 Data

Our empirical analysis uses the universe of cross-border M&A data from 1981 to 2016 provided by Thomson Reuters Security Data Company (SDC) Platinum.[14] In order to have sufficient cross-border M&A activity to study the neighborhood learning effects and the role of firms' accumulated experience, the estimation sample covers the period from 1995 to 2016. However, we utilize the full data beginning in 1981 to track the full history of companies' investments overseas. Moreover, due to incomplete information on deal valuations, we focus on the extensive margin of cross-border M&A, both in terms of the countries entered and the number of purchases made.

## 3.1 Macro-level descriptive statistics

Our sample includes 189 origin and 209 destination countries. From 1995 to 2016, an average of 8663 purchases are made annually around the world, with some minor fluctuations across years.[15] Appendix Table A.1 lists the top origin and destination countries across the sample period. Not surprisingly, developed countries dominate as the origin countries, with the US accounting for one-fifth of the aggregate cross-border acquisitions. However, developing countries like China and Malaysia rank as the 13th and 17th most common origin countries, respectively. Moreover, the distribution is heavily skewed, as 5 (15) origin countries contribute to almost 50% (75%) of all international M&A transactions. Targets are slightly more dispersed across destination countries, with 9 (24) destinations accounting for roughly 50% (75%) of sales. Investment into developed countries is generally more common, but large developing countries also serve as popular destinations. In particular, the BRICS countries (Brazil, Russia, India, China, and South Africa) are ranked 15th, 13th, 8th, 4th, and 29th, respectively.

Table 1 provides additional descriptive statistics. Because these statistics are generally skewed by the presence of large countries, we present both the mean and median, along with

[14]This database has previously used for the analysis of global cross-border investment activity in, for example, Rossi and Volpin (2004), di Giovanni (2005), Martynova and Renneboog (2008), Erel et al. (2012), and Chan and Zheng (2018).

[15]We drop all deals in which the name of the acquirer or target is "Investors", "Investor Group", "Shareholders", "Creditors", "US Dept of the Treasury", "Bondholders", "IFC", "Employee Stock Ownership Plan", or it contains the word "Undisclosed". We also exclude transactions in which either the origin or destination country is "Unknown" or "Multi-National".

Table 1: Descriptive Statistics at the Aggregate Level

| | Panel A: Origin countries | | |
|---|---|---|---|
| | Mean | Median | Std dev. |
| 1. Number of acquisitions across all years and destinations | 996 | 27 | 3569 |
| 2. Number of acquisitions across destinations per year | 80.2 | 8 | 216 |
| 3. Number of acquisitions per destination per year | 5.81 | 2 | 18.3 |
| 4. Number of destinations across all years | 31.0 | 12 | 38.6 |
| 5. Number of destinations per year | 13.8 | 6 | 17.8 |
| | Panel B: Destination countries | | |
| | Mean | Median | Std dev. |
| 1. Number of sales transactions across all years and origins | 901 | 85 | 2526 |
| 2. Number of sales transactions across origins per year | 54.9 | 7 | 136 |
| 3. Number of origins across all years | 28.1 | 22 | 22.9 |
| 4. Number of origins per year | 9.46 | 5 | 10.4 |

*Notes:* Authors' calculations using cross-border M&A data between 1995 and 2016 from Thomson Reuters SDC Platinum.

the standard deviation. For example, Panel A indicates that, on average, an origin country acquires close to 1000 companies abroad during this 22 year period. However, there is large variation across the sample, and the median number is much smaller at 27. For each origin-destination pair, the average number of annual transactions is 5.81.[16] At the extensive margin in terms of the number of destinations, origin countries enter around 14 foreign markets every year, which means that only a very small share of countries have bilateral investment in the form of M&A. Although this share has been increasingly slowly over time, over 90% of country pairs today do not have acquisitions in either direction. Helpman et al. (2008) document a similar, but less drastic, pattern for international trade, and the analogous graph to Figure I in Helpman et al. (2008) for cross-border M&A is presented in Figure 3.

### 3.2 Micro-level descriptive statistics

At the micro level, we analyze the impact of neighborhood learning effects in the third country for acquirers in the origin country and their choice of destination market. In order to define spatial networks, data on firms' locations is required. In SDC Platinum, city-level address information is by far the most available for firms in the US, making it the most suitable candidate as a third country to study the neighborhood learning effect. Data limitations unfortunately preclude us from examining micro-level networks or alternative sources of information in other countries. Therefore, we study non-US acquirers that make cross-border acquisitions in both the US and non-US destinations, and the spatial interactions of their US targets with neighboring participants in the cross-border M&A market.

Out of all global M&A transactions, the US is the origin (destination) country in 21% (13%) of the deals, and the remaining 66% are unaffiliated with the US.[17] Descriptive statistics for

[16]This is a bilateral statistic, so the number of acquisitions per destination per year for an origin country is exactly the same as the number of sales per origin per year for a destination country. Also, the statistics in Panel A rows 2 to 5 and Panel B rows 2 to 4 are computed excluding zeros. The inclusion of zeros lowers both the average and median while increasing the standard deviation, but magnitudes are similar to those shown in Table 1.

[17]Similar statistics for the period from 1990 to 2007 are provided by Erel et al. (2012). We exclude the territory

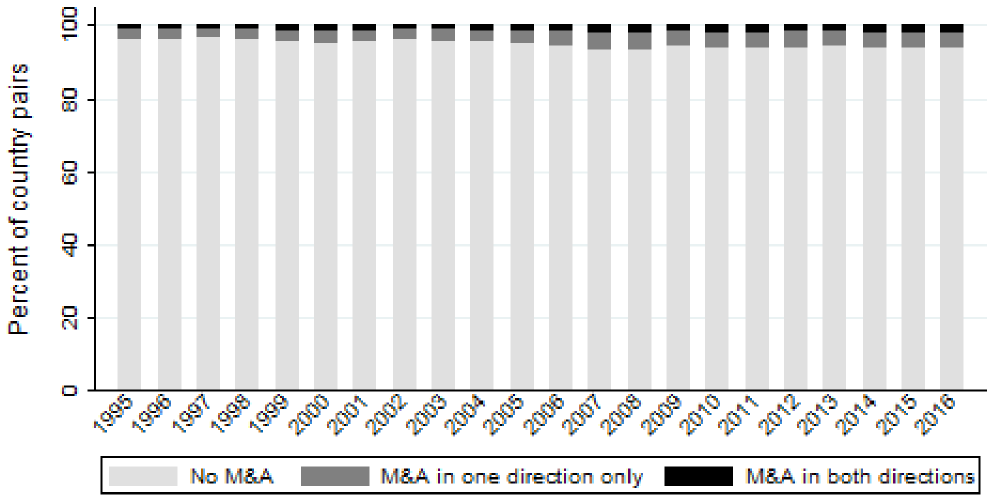



Figure 3: Distribution of country pairs based on direction of cross-border M&A. The sample contains 189 origin and 209 destination countries.

the micro-level analysis are presented in Table 2. We identify 2,832 non-US acquirers from 54 origin countries that make an acquisition at least once in the US, and subsequently, purchase at least one non-US target in a foreign country.[18] The two most common origin countries are the United Kingdom and Canada, which account for about 18% and 12% of the multinational firms, respectively. Other large origin countries include Germany, Japan, and France.[19] These firms account for a total of 9,387 cross-border M&A deals to 160 non-US destinations, and on average, they enter 1.96 (unique) destinations before buying a target in the US for the first time, and 2.85 non-US destinations after.

While SDC Platinum provides the vast majority of information on US firms' locations, in an effort to maximize coverage, we supplement it with data from Bloomberg L.P. (2018a,b). This online database maintains a repository of company profiles that are created and managed by S&P Global Market Intelligence. We deem the city information of SDC Platinum less reliable when street addresses are missing. For this set of firms and those that have the city missing entirely, we extract city and state information from Bloomberg L.P. (2018a,b) where available, and use it as a replacement.[20]

of Guam, Northern Mariana Islands, Puerto Rico, US Virgin Islands, as well as the Marshall Islands, which has been governed by the US in the past.

[18]To identify a firm, we use both the acquirer name ("an") and CUSIP code ("acu"). Because of the many-to-many correspondence between the two variables (e.g., the firm may change its name), we search across all firms and link those that share the same name or same CUSIP code.

[19]The remaining countries are: Algeria, Argentina, Australia, Austria, Bahamas, Bahrain, Belgium, Belize, Brazil, Bulgaria, China, Colombia, Cyprus, Denmark, Egypt, Finland, Greece, Hong Kong, Iceland, India, Indonesia, Ireland, Israel, Italy, Kazakhstan, Kuwait, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Qatar, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Arab Emirates, and Venezuela.

[20]We take multiple steps in this process: 1) We first use the website's search function to directly look up firms that have missing street addresses ("astr" or "tstr"). City and state information can be extracted with relative ease because they are displayed on different lines. However, some companies that exist in the database may not be found due to minor spelling mistakes or problems with Bloomberg's company name registry. 2) For the

Table 2: Descriptive Statistics at the Micro Level

| | Panel A: Non-US acquirers | | | |
|---|---|---|---|---|
| | Mean | Median | Std dev. | Total number |
| 1. Number of firms per origin country | 52.4 | 14 | 97.7 | 2832 |
| 2. Number of non-US destinations before entering US | 1.96 | 1 | 1.49 | |
| 3. Number of non-US destinations after entering US | 2.85 | 2 | 2.91 | |
| 4. Number of US locations per firm per year | 2.80 | 1 | 3.49 | |
| | Panel B: US neighboring acquirers | | | |
| | Mean | Median | Std dev. | Total number |
| 1. Number of firms per city | 6.31 | 1 | 38.8 | 14,585 |
| 2. Number of acquisitions per city across years | 4.51 | 2 | 5.41 | 36,279 |
| 3. Number of acquisitions per city per year | 3.48 | 1 | 12.7 | |
| | Panel C: US neighboring targets | | | |
| | Mean | Median | Std dev. | Total number |
| 1. Number of firms per city | 5.22 | 1 | 26.1 | 18,426 |
| 2. Number of sales transactions per city across years | 2.97 | 1 | 3.85 | 19,937 |
| 3. Number of sales transactions per city per year | 1.90 | 1 | 3.61 | |

Notes: Authors' calculations using cross-border M&A data for the US between 1995 and 2016 from Thomson Reuters SDC Platinum. Calculations for row 3 of Panels B and C use non-zero values only.

Abbreviations, alternate names, or spelling mistakes prevent us from simply matching the city information provided to a list of US cities with geographic coordinates (i.e., latitude and longitude). For example, we found that "South San Francisco" is in fact associated with "San Francisco South", "S San Fransisco", "So San Francisco", and 6 other misspelled versions. Thus, additional steps must also be taken here. We obtain two lists of cities and counties in the US from Geonames (2018), which contains coordinate information, as well as Grammakov et al. (2014), which does not. The combined dataset gives 64,209 locations in the US. A bigram matching algorithm is used to check for any overlapping locations (e.g., Miami and Miami-Dade County) or other errors in the data (e.g., Washington DC coded as Washington the state, or Delaware-incorporated companies coded with Delaware as the state). Finally, for all cities matched that still have missing coordinates, we either find the closest city from Geonames (2018), or search for the coordinates online. After this cleaning procedure, we obtain a list of 4,706 US locations (i.e., towns, cities, or counties) in which cross-border M&A activity is observed. The bilateral distance between locations is computed with ArcGIS. We rely on the driving distance as the main measure (94% of pairs), and the direct (great circle) distance where the quality of the road map is poor (6%).

In summary, we are able to identify the city and associated geographic coordinates in 36,279 (19,937) cross-border transactions involving a US acquirer (target). This corresponds to 96%

remaining set of companies, we perform probabilistic record linkage using a bigram matching algorithm (i.e., fuzzy matching) with the entire list of all US company names downloaded from Bloomberg. Specifically, we use Stata's reclink2 command with a minimum field-similarity score of 0.95 to find the best match. The matches (11,198 observations) are then manually inspected. Addresses of confirmed matches are then retrieved from Bloomberg. 3) With the addresses from steps 1 and 2, we first compare the state information, which is always given by SDC Platinum. We discard Bloomberg addresses for which the state does not match with SDC Platinum. 4) If the city is missing in SDC Platinum, we replace it with the city from Bloomberg. Otherwise (for 483 observations), we manually inspect and compare the city information provided, searching online for the correct city associated with the firm.

(83%) of the total number of US acquisitions (sales), where 1.2% (4.0%) of the observed locations were originally missing and recovered, and an additional 4.0% (10%) were corrected. Figures 4(a) and (b) show the geographic distribution of acquirers and targets, respectively. The size of the dots indicates the mass of firms, and the most popular source and host cities are New York and Houston. Targets are slightly more dispersed than acquirers. Appendix Table A.2 lists the top 20 cities with the most acquisitions made and targets sold throughout the sample period. Not surprisingly, both lists contain large cities and overlap heavily. As indicated in Table 2, each city has, on average, 6.31 acquirers (5.22 targets), though the standard deviation across locations is large. These companies account for roughly 3.48 acquisitions and 1.90 sales transactions every year in each city.

In Figure 4(c), we plot the locations of the targets purchased by the non-US acquirers, a subset of Figure 4(b). The distribution of this subset of targets is roughly similar to the entire sample. This suggests that our regression estimates of the neighboring learning effect are somewhat representative of the knowledge spillovers from US multinationals or foreign affiliates in the US.

# 4 Empirical framework

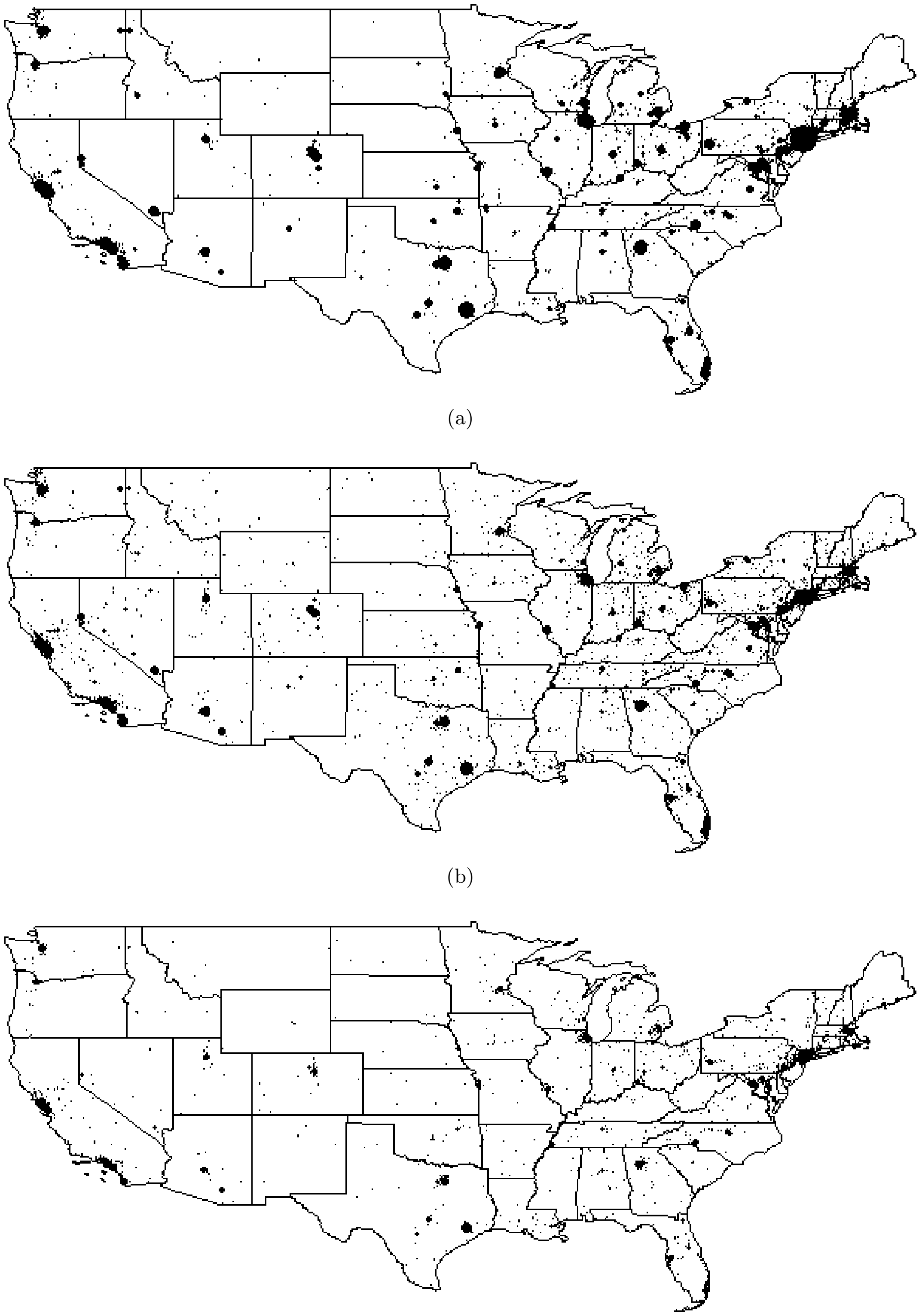
## 4.1 Macro-level regressions

We test the macro- and micro-level predictions of the model empirically using our global M&A data. At the aggregate level, we estimate the following regression equation:

$$\begin{aligned} A_{mnt} = B_0 + B_1 \sum_{r \neq m,n} W_{rn,t-1} A_{mr,t-1} + B_2 X_{mnt} + B_3 \sum_{r \in N(n)} A_{mrt} + B_4 A_{mn,t-1} \\ + c_m + c_n + c_t + \epsilon_{mnt}, \end{aligned} \tag{12}$$

where the dependent variable $A_{mnt}$ is the number of acquisitions from origin $m$ to destination $n$ at year $t$, and the regressor of interest is $\sum_{r \neq m,n} W_{rn,t-1} A_{mr,t-1}$, the weighted sum of acquisitions from $m$ to third countries $r$ in the previous year. We use measures of both geographic and economic closeness between $r$ and $n$ for the weights $W_{rn,t-1}$. These include the inverse of distance ($1/Distance_{rn}$), the volume of (lagged) cross-border M&A activity ($A_{rn,t-1}$ or $A_{nr,t-1}$), as well as combinations of the two variables.

In Eq. (12), we control for other determinants of cross-border M&A activity using a set of variables $X_{mnt}$ from a standard gravity model. These include the origin and destination's (log) real GDP, (log) distance, and indicator variables for sharing a border, legal origins, language, colonial ties, and a free trade agreement (FTA). Data are retrieved from the World Bank World Development Indicators, CEPII, La Porta et al. (1999), and de Sousa (2012). We also account for contemporaneous demand-side forces of $n$'s region $N(n)$ with the total number of acquisitions to the neighboring countries of $n$, $\sum_{r \in N(n)} A_{mrt}$. A neighboring country of $n$ (which



(a)

(b)

(c)

Figure 4: This figure shows, from 1995 to 2016, the locations of (a) US acquirers; (b) all US targets; (c) US targets of 2,832 non-US acquirers in estimation sample. Hawaii and Alaska are excluded from the figure but included in the estimation sample.

excludes $n$ itself) is either contiguous, separated by less than 500km, or the closest country.[21] In addition, given the persistence of cross-border investment, the lagged dependent variable $A_{mn,t-1}$ is included as a regressor. Lastly, we control for unobserved heterogeneity using origin, destination, and year fixed effects.

In estimating Eq. (12), we use logarithms of the regressors $\sum_r W_{rn,t-1}A_{mr,t-1}$, $\sum_{r\in N(n)} A_{mrt}$, and $A_{mn,t-1}$. To retain observations with zero counts of M&A in these explanatory variables, the constant of 1 is added before taking logarithms. Moreover, as shown in Figure 3, the share of country pairs with positive cross-border M&A investment is small. The large incidence of zeros generates over dispersion in the dependent variable, as the standard deviation of M&A counts is roughly 10 times larger than the mean. Hence, we estimate a negative binomial regression (e.g., Davies et al., 2015). Standard errors are clustered by origin-destination pair.

### 4.2 Micro-level regressions

At the micro level, we examine a set of non-US acquirers and their choice of non-US destinations for cross-border M&A. We are interested in studying the impact of their US targets' neighbors on this choice, and how this effect varies with their accumulated experience abroad. Thus, we estimate the following linear probability model:

$$Pr(\mathbf{1}[acquirer]_{imnt}=1) = b_0 + b_1 d_{imn,t-1} + b_2 D_{imn,t-1} + b_3 Locations_{imr,t-1} + b_4 X_{mnt} \quad (13)$$
$$+ b_5 A_{-m,nt} + b_6 \sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0} + c_i + c_n + c_t + e_{imnt}.$$

The dependent variable is an indicator variable equal to 1 if firm $i$ from origin $m$ makes at least one acquisition in destination $n$ at time $t$. We follow Fernandes and Tang (2014) and Kamal and Sundaram (2016) to examine firms' destination choice conditional on entering foreign markets after investing in the US.[22] The set of destinations $n$ for firm $i$ include new destinations with at least one US acquisition or sale in the previous year The regressor of interest for the third-country neighborhood learning effect is $d_{imn,t-1}$, i.e., the number of neighboring firms near acquirer $i$'s US target that made an acquisition in destination $n$ last year. While the duration of learning may vary, the neighboring cross-border M&A activity of the previous year is arguably

[21] For example, the neighbors of the United Kingdom are Ireland, Belgium, France, Germany, Luxembourg, and the Netherlands. Ireland is contiguous to the United Kingdom, while bilateral distances to the remaining countries are 324, 343, 495, 494, and 360km respectively. A country such as Japan does not share a border with any other nation, and the distances between Japan and all other countries are greater than 500km. Although Korea is 1,157km away, it is the closest country to Japan, and therefore, assigned as its neighbor.

[22] In order for there to be sample selection bias with regards to entry either into or out of the US, unobservables that influence these firm-specific entry margins must be correlated with the destination-specific M&A activity of US neighboring firms. For example, consider China as the origin country, and Korea as the destination of interest. A Chinese acquirer may not enter the US because it is already close to Korea. If it were to enter the US, it may choose to enter locations that have a lot of cross-border M&A activity with Korea. However, the determinants of entry into Korea are controlled by $X_{mnt}$, the set of gravity equation variables, and are therefore not unobserved. As we discuss below, $X_{mnt}$ and $A_{-m,nt}$ (i.e., the number of acquisitions to $n$ from all other countries) accounts for both a market-specific as well as global hierarchy of destinations. Thus, it is highly unlikely for unobservables that affect firm entry from an origin country to a non-US destination to be unrelated to the market or geographic characteristics of either country.

the most relevant and therefore also the most valuable for the acquirer. In addition, we consider the network influence of neighboring targets with $\delta_{imn,t-1}$ as defined by Eq. (9b). The impact of accumulated experience is captured by $D_{imn,t-1}$, the firm-level weighted sum of acquisitions to third countries up to time $t-1$ (excluding the US). As discussed in Section 5.2.4 below, the same weights from the macro-level regression Eq. (12), $W_{rn,t-1}$, are employed. The number of US target locations that the acquirer has, $Locations_{imr,t-1}$, corresponds to $G^A_{imr}$ in the theoretical model.

Our estimation examines the impact of networks in US, a third country, on the acquisition decisions of firms in origin $m$ to destination $n$. Arguably, any endogeneity problems of this regression related to demand and/or supply shocks are less severe compared to a study of the domestic neighborhood learning effect in country $m$, in which an acquirer and firms within its spatial network would face similar shocks. Common supply-side shocks that affect both the acquirer and the neighbors of its US target are unlikely as they are situated in different countries. On the destination demand side, we rule out plausible sources of omitted variable bias by including the same set of regressors $X_{mnt}$ as the macro-level regression to account for traditional gravity forces, and the number of contemporaneous acquisitions by all non-$m$ non-US countries to destination $n$, $A_{-m,nt}$. By controlling for these time-variant destination characteristics, we limit the bias to demand shocks that must have a similar impact simultaneously on the origin country and the US, without having the same effect on other countries. The occurrence of such pairwise demand shocks also seems improbable. In addition, the inclusion of variables such as market size in $X_{mnt}$ and $A_{-m,nt}$ allows for the possibility of a global hierarchy of destinations, in which the ranking of destination market potential would be identical for firms from different origin countries (i.e., non-US and US).

In the model, firms are assumed to behave myopically, and enter third countries without considering the future impact of learning about other countries. Because Canada and Mexico are both geographically and economically close to the US (e.g., through NAFTA), the regressions may suffer from sample selection bias if foreign firms enter the US with motivations of either expanding operations into these two neighboring countries or learning about them. However, in the data, only 3.6% and 1.6% of all cross-border M&A deals from outside the US are directed to Canada and Mexico, respectively, as ensuing destinations after the US. Thus, the empirical analysis treats firms' decision to enter the US as largely exogenous.

We must, however, take into account the endogeneity problem associated with the acquirer firm's choice of target location *within* the US. That is, the non-US acquirer may purchase a US target in a particular location for the purpose of learning about their destination of interest. We take several steps to alleviate this potential endogeneity concern. First, given such motivations by the acquirer, one might expect its next acquisition to occur soon after its entry into the US. The data indicates that firms, on average, wait 4.47 years (standard deviation 4.71) after the entering the US before investing in a new non-US destination. This is not an insignificant period of time, and is also slightly higher than the global average of 2.58 years. Second, we address this endogeneity problem explicitly in our regression analysis by treating it as an omitted variable bias. If firms are driven to learn about foreign destinations by entering a US city, or are attracted by the presence of industry clusters, we should observe substantial cross-border M&A activity to the destination of interest in both directions from the firms of that city *before* the non-US acquirer enters the US. Therefore, we include as regressors (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$ as well as (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{target}]_{jrn,t_0}$, i.e., the number of neighboring acquirers and targets, respectively, to destination $n$ at time $t_0$, the year before acquirer $i$'s entry in the US. We also employ an instrumental variable (IV) strategy to demonstrate the robustness of our main findings, which we discuss below in Section 5.2.1.

Lastly, to further mitigate endogeneity concerns, Eq. (13) includes firm fixed effects $c_i$ to control for unobserved firm-level heterogeneity (e.g., productivity), destination fixed effects $c_n$ for the time-invariant characteristics of destination countries, and year fixed effects $c_t$ to capture any global shocks to cross-border investment. Because firms operate in a single sector as observed in our data, firm fixed effects absorb sector (and origin country) fixed effects. In robustness checks, we also employ origin-destination pair fixed effects, as well as destination-year, origin-year, and firm-year fixed effects. Due to the inclusion of firm fixed effects and the incidental parameters problem, we estimate Eq. (13) with ordinary least squares (OLS), and cluster standard errors at the firm (i.e., acquirer) level.

# 5 Empirical results

## 5.1 Macro-level regression results

We provide preliminary evidence of learning effects in third countries at the aggregate level in Table 3. Across the columns, we consider various weights $W_{rn,t-1}$ to measure the geographic and economic closeness of third country $r$ to destination $n$. First, in column 1, we simply sum up the (lagged) number of acquisitions from origin $m$ to all third countries $r$, assigning an equal weight of 1 to these prior destinations. The estimate indicates that a 1% increase in the number of acquisitions to third countries raises the number of acquisitions globally from $m$ by about 0.2%. The results from the remaining columns of Table 3 lend strong support to Proposition 1. In columns 2 and 3, we use the inverse of distance ($1/Distance_{rn}$) and the number of acquisitions from $r$ to $n$ ($A_{rn,t-1}$) as weights, respectively. Holding the number of acquisitions to third countries fixed, a 1% decrease in total distance from third countries $r$ to $n$ increases the number of acquisitions from $m$ to $n$ by around 0.3%. Likewise, a 1% increase in the number of lagged acquisitions from $r$ to $n$ raises $A_{mnt}$ by roughly 0.2%.

Next, in column 4, we combine the two weights as $A_{rn,t-1}/Distance_{rn}$ to reflect both proximity and cross-border economic interaction. Column 5 instead utilizes the number of sales from $r$ to $n$, $A_{nr,t-1}$ (equivalently, the number of acquisitions from $n$ to $r$), and column 6 again combines it with distance. Smaller marginal effects are observed in columns 5 and 6 compared to columns 3 and 4. However, the results are robust for all measures of closeness, and suggests that experience in third countries, proxied by the weighted sum of previous acquisitions, has a positive impact on aggregate M&A activity into the destination of interest.

Table 3: Aggregate Experience and Number of Acquisitions

| Weight $W_{rn,t-1}$: | Equal<br>(1) | $\frac{1}{Distance_{rn}}$<br>(2) | $A_{rn,t-1}$<br>(3) | $\frac{A_{rn,t-1}}{Distance_{rn}}$<br>(4) | $A_{nr,t-1}$<br>(5) | $\frac{A_{nr,t-1}}{Distance_{rn}}$<br>(6) |
|---|---|---|---|---|---|---|
| (log) $\sum_r W_{rn,t-1} A_{mr,t-1}$ | 0.218*** | 0.291*** | 0.192*** | 0.151*** | 0.128*** | 0.100*** |
| | (7.79) | (14.12) | (14.92) | (16.66) | (13.13) | (15.23) |
| (log) GDP$_{mt}$ | 0.926*** | 0.753*** | 0.946*** | 0.972*** | 1.166*** | 1.164*** |
| | (10.53) | (8.88) | (11.83) | (12.46) | (14.17) | (14.45) |
| (log) GDP$_{nt}$ | 0.193*** | 0.193*** | 0.040 | 0.041 | -0.015 | -0.005 |
| | (3.74) | (3.84) | (0.79) | (0.81) | (-0.28) | (-0.10) |
| (log) Distance$_{mn}$ | -0.603*** | -0.509*** | -0.580*** | -0.551*** | -0.583*** | -0.562*** |
| | (-26.13) | (-21.35) | (-25.22) | (-23.65) | (-25.60) | (-24.56) |
| Land border$_{mn}$ | 0.093 | 0.127 | 0.108 | 0.117 | 0.093 | 0.104 |
| | (1.34) | (1.90) | (1.61) | (1.78) | (1.40) | (1.58) |
| Legal$_{mn}$ | 0.325*** | 0.320*** | 0.312*** | 0.309*** | 0.299*** | 0.302*** |
| | (10.22) | (10.24) | (9.90) | (9.94) | (9.59) | (9.78) |
| Language$_{mn}$ | 0.434*** | 0.418*** | 0.419*** | 0.414*** | 0.428*** | 0.420*** |
| | (9.06) | (8.90) | (8.67) | (8.75) | (8.94) | (8.93) |
| Colonial ties$_{mn}$ | 0.375*** | 0.356*** | 0.391*** | 0.380*** | 0.382*** | 0.372*** |
| | (5.71) | (5.53) | (5.92) | (5.83) | (5.79) | (5.74) |
| FTA$_{mnt}$ | 0.213*** | 0.185*** | 0.214*** | 0.191*** | 0.220*** | 0.203*** |
| | (6.40) | (5.60) | (6.37) | (5.72) | (6.64) | (6.17) |
| (log) $A_{mn,t-1}$ | 0.599*** | 0.590*** | 0.560*** | 0.570*** | 0.563*** | 0.573*** |
| | (28.84) | (29.15) | (25.86) | (27.94) | (26.73) | (28.73) |
| (log) $\sum_{r \in N(n)} A_{mrt}$ | 0.172*** | 0.129*** | 0.150*** | 0.138*** | 0.157*** | 0.147*** |
| | (12.87) | (9.96) | (11.45) | (10.77) | (12.10) | (11.41) |
| Origin FE | Y | Y | Y | Y | Y | Y |
| Destination FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| N | 249,517 | 249,517 | 249,517 | 249,517 | 249,517 | 249,517 |

*Notes:* In all columns, regressions are estimated using the negative binomial model, and the dependent variable is the number of acquisitions from $m$ to $n$ at time $t$, $A_{mnt}$. $T$-statistics are in parentheses, with standard errors clustered by origin-destination pair. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Consistent with literature (e.g., Blonigen and Piger, 2014), Table 3 also demonstrates that greater international M&A activity is observed between larger origin and destination countries that are geographically less distant with common legal origins, language, colonial ties, and a free trade agreement. Cross-border M&A is highly persistent and autocorrelation is strong, as a 1% increase in lagged acquisitions increases current acquisitions by around 0.6%. The number of acquisitions to a destination is also highly correlated with purchases to its neighboring region.

## 5.2 Micro-level regression results

### 5.2.1 Neighborhood learning effect

We now proceed to evaluate the theoretical implications of the model empirically at the micro level, beginning with the third-country neighborhood learning effect. For acquirer $i$ from origin $m$, micro-level signals are observed from neighboring acquirers and targets of its US target, denoted as $d_{imn,t-1} = $ (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t-1}$ and $\delta_{imn,t-1} = $ (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t-1}$, respectively. Again, the constant of 1 is added before taking logarithms of any explanatory variables involving counts of M&A deals. Our baseline measure of a target's neighborhood, $N(i\text{'s } target)$, is a 100km radius around its location. As points of reference, the distance from San Francisco to San Jose is 69km, Philadelphia to New York is 166km, and Houston to Austin is 233km. Table 4 provides estimates of the third-country neighborhood learning effect for both directions, with acquisitions in Panel A and sales in Panel B. The results are strongly supportive of Proposition 2, as the coefficients on the regressors of interest, $d_{imn,t-1}$ and $\delta_{imn,t-1}$, are positive and statistically significant across all columns (at the 1% level). Thus, the empirical evidence demonstrates the impact of the third-country spatial networks on firms' destination choice, and implies substantial knowledge spillovers that are transferred to the acquirer in the origin country.

Throughout, we ensure our results are not driven by other determinants of cross-border M&A activity by including the same set of variables for the gravity equation, $X_{mnt}$, as well as the number of acquisitions from non-origin (and non-US) countries to the destination $A_{-mnt}$.[23] In column 2, we account for the potential endogeneity of target location choice using (log) $\sum_{j \in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$ and (log) $\sum_{j \in N(i\text{'s } target)} \mathbf{1}[\widehat{target}]_{jrn,t_0}$. These are the purchases and sales of the target's neighborhood in the year before the acquirer's entry into the US. While these past purchases and sales at $t_0$ are both strongly correlated with their $t-1$ values at 0.773 and 0.766, respectively, the impact of the latter on firms' contemporaneous destination choice remains statistically significant. The high correlation between past and present M&A activity may be explained by domestic knowledge spillovers across the US acquirers and targets themselves. This is documented for exporters and importers in, for instance, Fernandes and Tang (2014), Kamal and Sundaram (2016), and Bisztray et al. (2017). While we do not focus on the local diffusion of information between domestic firms, the propagation of these externalities over time would be consistent with our results.

In column 3, we employ bilateral country-pair fixed effects to control for unobserved heterogeneity between origin and destination countries. To account for time-variant demand and supply shocks, columns 4 and 5 include the combinations of destination-year with origin-year and firm-year fixed effects, respectively. Because we observe destination choices for many firms across multiple years after their entry into the US, the regression does not suffer from perfect collinearity even with the inclusion of firm-year fixed effects. The main findings are also robust to these alternative specifications.

In column 6, we further address concerns of endogeneity using an IV strategy. We need an instrument that can predict not only where in the US acquirer $i$ from origin $m$ will invest, but also, the M&A activity of that US location to the destination of interest. Furthermore, the prediction of the US location choice must be independent of the destination of interest to satisfy the exclusion restriction. Our IV strategy relies on county-level historical migrant population data in the US. Prior literature has found the size of social networks formed by migration from the origin to destination country to have a positive impact on bilateral cross-border trade or FDI (e.g., Burchardi et al., 2017; Cohen et al., 2017). In particular, the historical migrant pop-

[23]Because the impact of the gravity equation variables on the probability of firm entry and the aggregate number of acquisitions from the macro-level regressions are qualitatively similar, we omit their coefficients from the regression tables. Full results for all tables are available upon request.

Table 4: Neighborhood Learning Effects in the US

| | Panel A: Neighboring acquirers | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $d_{imn,t-1}$ = (log) $\sum_{j\in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t-1}$ | 0.0063*** | 0.0042*** | 0.0041*** | 0.0028*** | 0.0030*** | 0.0142*** |
| | (12.23) | (7.56) | (7.32) | (4.76) | (4.99) | (3.74) |
| (log) Locations$_{imr,t-1}$ | -0.0017*** | -0.0024*** | -0.0024*** | -0.0020*** | | -0.0035*** |
| | (-2.78) | (-3.82) | (-3.73) | (-3.10) | | (-4.62) |
| (log) $A_{-mnt}$ | 0.0025*** | 0.0025*** | 0.0035*** | | | 0.0019*** |
| | (8.27) | (8.58) | (11.96) | | | (5.18) |
| (log) $\sum_{j\in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$ | | 0.0024*** | 0.0027*** | 0.0028*** | 0.0029*** | -0.0016 |
| | | (4.16) | (4.50) | (4.65) | (4.71) | (-0.98) |
| (log) $\sum_{j\in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t_0}$ | | 0.0033*** | 0.0035*** | 0.0037*** | 0.0037*** | 0.0004 |
| | | (3.49) | (3.75) | (3.87) | (3.83) | (0.30) |
| Controls: | GDP, Distance, Land border, Legal, Language, Colonial ties, FTA | | | | | |
| Firm FE | Y | Y | Y | Y | | Y |
| Destination FE | Y | Y | | | | Y |
| Year FE | Y | Y | Y | | | Y |
| Origin-Destination FE | | | Y | | | |
| Destination-Year FE | | | | Y | Y | |
| Origin-Year FE | | | | Y | | |
| Firm-Year FE | | | | | Y | |
| Underidentification test ($p$-value) | | | | | | < 0.01 |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.061 | 0.050 | 0.053 | |

| | Panel B: Neighboring targets | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta_{imn,t-1}$ = (log) $\sum_{j\in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t-1}$ | 0.0067*** | 0.0032*** | 0.0033*** | 0.0034*** | 0.0033*** | 0.0408*** |
| | (8.27) | (3.69) | (3.73) | (3.56) | (3.51) | (3.71) |
| (log) Locations$_{imr,t-1}$ | -0.0009 | -0.0020*** | -0.0020*** | -0.0018*** | | -0.0031*** |
| | (-1.52) | (-3.24) | (-3.18) | (-2.77) | | (-4.37) |
| (log) $A_{-mnt}$ | 0.0028*** | 0.0028*** | 0.0038*** | | | 0.0025*** |
| | (9.52) | (9.32) | (12.66) | | | (8.26) |
| (log) $\sum_{j\in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$ | | 0.0036*** | 0.0038*** | 0.0033*** | 0.0035*** | -0.0027 |
| | | (6.37) | (6.52) | (5.79) | (5.93) | (-1.39) |
| (log) $\sum_{j\in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t_0}$ | | 0.0032*** | 0.0034*** | 0.0032*** | 0.0033*** | -0.0121*** |
| | | (3.30) | (3.48) | (3.26) | (3.27) | (-2.62) |
| Controls: | GDP, Distance, Land border, Legal, Language, Colonial ties, FTA | | | | | |
| Firm FE | Y | Y | Y | Y | | Y |
| Destination FE | Y | Y | | | | Y |
| Year FE | Y | Y | Y | | | Y |
| Origin-Destination FE | | | Y | | | |
| Destination-Year FE | | | | Y | Y | |
| Origin-Year FE | | | | Y | | |
| Firm-Year FE | | | | | Y | |
| Underidentification test ($p$-value) | | | | | | < 0.01 |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.061 | 0.050 | 0.053 | |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. Columns 1 to 5 are estimated with OLS, and column 6 reports the second stage IV estimates. $T$-statistics are in parentheses, with standard errors clustered at the firm level. The $p$-values associated with the Kleibergen-Paap rank Lagrange Multiplier test statistic for the underidentification test are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

ulation has been used as an instrument for identification. Data on migrant populations in the US is obtained from IPUMS (Ruggles et al., 2018) for the year 1940, in which the residence of individuals is reported at the county level, and matched to the observed locations (i.e., towns, cities, counties) of our sample using the information provided by Geonames (2018). Acquirer $i$ from origin $m$ is expected to enter locations with larger migrant populations from its home country. We denote (log) $Pop^g_{mr}$ as the population of migrants from country $m$ to the US in the county $g$ of $i$'s target (averaged across counties if $i$ has multiple US target locations). Note that this variable is orthogonal to any characteristics of the destination market. By the same logic, the population of destination country $n$'s migrants in the US within the county of $i$'s target, (log) $Pop^g_{nr}$, may be used to predict cross-border M&A activity between US locations and the destination of interest. Hence, our instrument is the interaction variable (log) $Pop^g_{mr}$ $\times$ (log) $Pop^g_{nr}$. The first-stage estimates presented in Appendix Table A.3 demonstrate that our instrument is highly correlated with both micro-level signals, i.e., the number of neighboring acquirers to or targets of the destination of interest. Importantly, the second-stage regression results in Table 4 column 6 are consistent with our previous findings, and suggest strong neighborhood learning effects.

Next, we compare the magnitudes of the neighborhood learning effects for both directions. In the theoretical model, we remained agnostic about the strength of each learning channel, and assumed that both micro-level signals are drawn from the same (prior) distribution. Empirically, the effects are comparable in magnitude, as neither the coefficients of Table 4 Panel A nor B are uniformly larger than the other. From the baseline specification in column 2, a one-standard-deviation increase in the (lagged) number of neighboring acquirers (targets) to the destination, or 5.67 (3.00) firms, raises the probability of acquisition by around 1.6 (0.7) percentage points. Given that the unconditional probability of entry into a destination is roughly 1.7 percentage points, this implies that the neighborhood learning effects are also economically significant.[24]

In Table 5, we provide empirical evidence supportive of Propositions 3 and 4. First, in column 1, we jointly study the micro-level signals received from neighboring acquirers and targets. Compared to the baseline specification, we find that the individual impact of each channel falls, but both sources of knowledge spillovers remain significant for the acquirer's destination choice. Next, we interact the two neighborhood learning effects in column 2. Consistent with Proposition 3, the learning effects are complementary, as the coefficient of the interaction term is positive and statistically significant. Thus, when the acquirer receives stronger signals about a destination from its third-country neighboring acquirers, the marginal impact of neighboring targets on its destination choice is also larger, and vice versa. In columns 3 and 4, we test Proposition 4 by interacting each of the micro-level signals with the number of target locations in the US. Although the individual effects of the micro-level signals lose significance, the interaction terms are positive and statistically significant. The results imply that the information

[24] The beta coefficient on $d_{imn,t-1}$ ($\delta_{imn,t-1}$) from a regression with standardized values is 0.0033 (0.0018). The standard deviation of (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t-1}$ ($\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{target}]_{jrn,t-1}$) is 0.79 (0.56), which is equivalent to $e^{0.79} - 1 = 1.20$ (0.75) neighboring firms. Thus, for a one-standard-deviation increase in the number of neighbors, the marginal effect is $5.67 \div 1.20 \times 0.0033 = 0.016$ ($3.00 \div 0.75 \times 0.0018 = 0.007$).

Table 5: Interaction Effects and Intensity with Number of Locations

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $d_{imn,t-1}$ | 0.0039*** | 0.0030*** | 0.0005 | |
| | (6.86) | (4.81) | (0.70) | |
| $\delta_{imn,t-1}$ | 0.0021** | -0.0006 | | -0.0010 |
| | (2.42) | (-0.55) | | (-0.86) |
| $d_{imn,t-1} \times \delta_{imn,t-1}$ | | 0.0017*** | | |
| | | (2.66) | | |
| $d_{imn,t-1}$ × (log) $\text{Locations}_{imr,t-1}$ | | | 0.0042*** | |
| | | | (9.23) | |
| $\delta_{imn,t-1}$ × (log) $\text{Locations}_{imr,t-1}$ | | | | 0.0041*** |
| | | | | (5.68) |
| Controls | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 | 0.044 |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. All regressions are estimated with OLS, and include controls for GDP, Distance, Land border, Legal, Language, Colonial ties, FTA, (log) $\text{Locations}_{imr,t-1}$, (log) $A_{-mnt}$, (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$, and (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{target}]_{jrn,t_0}$. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

obtained through spillovers at different locations may be used as validation for the knowledge gained elsewhere. In other words, the greater the number of information sources, the stronger the impact of each individual source. This reflects an advantage of having wider exposure to different spatial networks of the target companies in the third country.

### 5.2.2 Heterogeneity of networks

In the theoretical model, weights $w_{ijr}$ capture the importance of neighboring firms to the foreign acquirer's US target. Empirically, we exploit the heterogeneity of firms in the target's spatial network to gain further insights on the neighborhood learning effect. In particular, we vary the definition of neighbors with respect to geographical aspects and industrial composition. First, in Table 6 column 1, we decompose neighboring firms within the 100km radius by state borders. Hence, the M&A activity of firms is split between those that reside in the same state, and those that operate in a different state. We restrict the sample to non-US acquirer firms with targets in locations within 100km of a state border. Non-acquirers with targets only in the states of Alaska and Hawaii are also excluded based on this criterion. The coefficients of $d_{imn,t-1}$ and $\delta_{imn,t-1}$ are statistically significant only for neighboring firms within, as opposed to outside, state borders, and the magnitudes of the learning effects are also much larger for the former group. This suggests a strong border effect in impeding the diffusion of knowledge, and that the interactions between firms are likely more common within state boundaries.

In Table 6 columns 2 and 3, we study the role of industrial linkages between the non-US acquirers and firms in the spatial networks of their US targets. We begin with a simple decomposition of neighboring firms that operate in the same and different sectors as the acquirer

Table 6: Heterogeneity of Networks

| | Panel A: Neighboring acquirers | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $d_{imn,t-1}$ (same state) | 0.0050*** | | |
| | (7.14) | | |
| $d_{imn,t-1}$ (different state) | 0.0003 | | |
| | (0.35) | | |
| $d_{imn,t-1}$ (same sector) | | 0.0067*** | |
| | | (7.51) | |
| $d_{imn,t-1}$ (different sector) | | 0.0020*** | |
| | | (3.34) | |
| $d_{imn,t-1}$ (upstream sector) | | | 0.0002 |
| | | | (0.15) |
| $d_{imn,t-1}$ (downstream sector) | | | 0.0033** |
| | | | (2.00) |
| Controls | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y |
| N | 326,719 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 |
| | **Panel B: Neighboring targets** | | |
| | (1) | (2) | (3) |
| $\delta_{imn,t-1}$ (same state) | 0.0056*** | | |
| | (5.09) | | |
| $\delta_{imn,t-1}$ (different state) | -0.0013 | | |
| | (-0.77) | | |
| $\delta_{imn,t-1}$ (same sector) | | 0.0084*** | |
| | | (6.07) | |
| $\delta_{imn,t-1}$ (different sector) | | 0.0005 | |
| | | (0.50) | |
| $\delta_{imn,t-1}$ (upstream sector) | | | -0.0057** |
| | | | (-2.34) |
| $\delta_{imn,t-1}$ (downstream sector) | | | 0.0082*** |
| | | | (3.24) |
| Controls | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y |
| N | 326,719 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. All regressions are estimated with OLS, and include controls for GDP, Distance, Land border, Legal, Language, Colonial ties, FTA, (log) Locations$_{imr,t-1}$, (log) $A_{-mnt}$, (log) $\sum_{j \in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$, and (log) $\sum_{j \in N(i\text{'s } target)} \mathbf{1}[\widehat{target}]_{jrn,t_0}$. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

in column 2. The SDC Platinum database classifies all firms into one of 84 industries at the SIC 2-digit level (as well as the narrower 4-digit level). However, for our purposes, this narrow definition of sectors is not useful. Besides, for example, the finance or business services industries, the prevalence of neighboring firms that share the same industry at the 2-digit level is very small. By aggregating industries into one of 9 SIC 1-digit sectors, around 27% (28%) of US neighboring acquirers (targets) are classified in the same sector as the non-US acquirer. We find that neighboring firms operating in the same sector account for much of the impact from the target's spatial networks. In Panel A, the within-sector marginal effect is several times larger, and in Panel B, the impact of neighboring targets in different sectors disappears entirely. As with state boundaries, this evidence suggests that there are varying degrees of knowledge spillovers from the target's spatial network to the foreign acquirer. Information provided by firms with similar characteristics, such as sector classification, are more relevant and have greater impact.

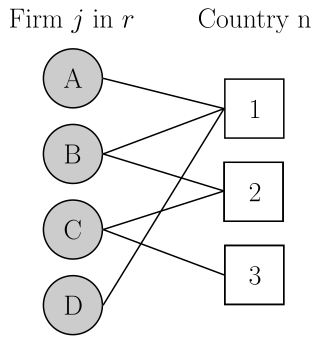
The group of neighboring firms operating in different sectors is large, and the estimates of column 2 mask the potential heterogeneity that exists within this subset of the spatial network. Hence, we further decompose the neighbors of column 2 into two groups, depending on their position in the supply chain relative to foreign entrant $i$. From the Bureau of Economic Analysis (BEA), we obtain the US 1996 annual input-output (I-O) accounts published in the Survey of Current Business, January 2000, which provides the use of commodities by sectors at the same SIC 1-digit level.[25] The data table is replicated in Appendix Figure A.1. Because column 2 of Table 6 already investigated the role of firms in the same sector, we classify input-output linkages only for sectors that are different. Thus, for a particular sector, we define the top four sectors supplying intermediate goods as upstream. Likewise, the top four buyers or users of intermediates are downstream sectors. Table 6 column 3 reports large and statistically significant effects for neighboring firms making foreign purchases or sales in downstream sectors, and not in upstream sectors. The results suggest an asymmetry with respect to upstream and downstream linkages in determining the acquirer's destination choice. In particular, information about sales in the destination market is more valuable than knowledge on suppliers of intermediate goods for production.

### 5.2.3 Network centrality of neighboring firms

In this section, we take another direction to examine the heterogeneity of the neighborhood learning effect by incorporating the variation of neighboring firms' past cross-border M&A experience to compute weights $w_{ijr}$ for $d_{imn,t-1}$ and $\delta_{imn,t-1}$ in Eq. (9). Up to now, neighboring acquirers or targets receive a weight of either 1 or 0. However, this does not reflect the degree of importance for each firm within the spatial network, and the potentially unequal diffusion of knowledge to acquirer $i$. Intuitively, more experienced neighbors may be able to share information that is more useful than neighbors that have had less success overseas, and their signals should be weighted more heavily. To measure neighboring firms' experience and therefore their importance, we take a network perspective to examine the central position of each firm in the global M&A network. Specifically, we construct this global M&A network as a two-mode (bipartite) network (Faust, 1997; Borgatti and Everett, 1997). Firms and countries stand for two separate camps of the network, and links are formed between firms and countries with cross-border acquisitions. There are no links within a mode of this two-mode network, i.e., amongst firms or amongst countries.

Figure 5 provides a simple illustration of a two-mode M&A network of four acquirer firms and three countries. According to Panel (a), firm A invests in country 1; firm B invests in

[25] See `https://www.bea.gov/industry/historical-industry-accounts-data`.




(a)

| Firm / Country | 1 | 2 | 3 | Row sum |
|---|---|---|---|---|
| A | 1 | 0 | 0 | 1 |
| B | 1 | 1 | 0 | 2 |
| C | 0 | 1 | 1 | 2 |
| D | 1 | 0 | 0 | 1 |
| Column sum | 3 | 2 | 1 | |

(b)

| | A | B | C | D | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|
| A | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| B | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| C | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| D | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |

(c)

Figure 5: This figure depicts a two-mode M&A network of firms and countries as: (a) an undirected graph; (b) an incidence matrix; and (c) a bi-adjacency matrix.

countries 1 and 2; firm C invests in countries 1 and 3; and firm D invests in country 1. We have drawn undirected links in this figure, but in application, we use directed links and construct weights separately for the US neighboring acquirers and targets. Following the conventional network (graph) analysis, this two-mode network can be presented as an incidence matrix in Panel (b), and based on this incidence matrix, we can obtain the number of connections of each firm from the row sum ([1, 2, 2, 1]') and the number of connections of each country from the column sum ([3, 2, 1]). These numbers of connections represent the degree centrality of each firm and country, respectively.

Furthermore, we can extend this incidence matrix to a bi-adjacency matrix in Panel (c) of Figure 5. Using this square bi-adjacency matrix, we can compute the eigenvector centrality for each firm and each country following the spectral analysis of Borgatti and Everett (1997).[26] In our application, eigenvector centrality is preferred to degree centrality because it captures the importance of each firm proportional to the importance of each country that it invests in. In

[26]Based on the square bi-adjacency matrix, the eigenvector centrality is computed as the eigenvector with respect to the largest eigenvalue.

other words, eigenvector centrality goes beyond merely counting the number of connections by considering the structure of the whole network when evaluating the quality of each link. For example, in the M&A network of Figure 5, country 1 is more important than country 2, which in turn is more important than country 3. This is because three firms enter country 1, two firms enter country 2, and only one firm enters country 3. A higher eigenvector centrality is associated with investing in country 1 than the two other countries. Consequently, although both firms B and C invest in two countries, the eigenvector centrality of firm B (0.5) is higher than C (0.29) because B invests in country 1 while firm C does not. Firm B will also have a higher eigenvector centrality than firms A and D (0.29) because it enters more destinations.

We construct the two-mode incidence matrix using the global M&A investment transaction records available beginning in 1981. Each transaction establishes a link between a firm and a country. To capture the experience of firms, we let this link persist to the end of the sample period. As mentioned, we distinguish the links built by purchases and sales. On the buying (selling) side, the M&A network is built between an acquirer (target) firm and a target (source) country. Using the corresponding bi-adjacency matrices, we then compute the eigenvector centrality for each US acquirer (target) firm $j$ in each year, and use them as weights for the measure of the neighborhood learning effect $d_{imn,t-1} = (\log) \sum_{j \in N(i\text{'s } target)} w_{ijr,t-1} \mathbf{1}[\widehat{acquirer}]_{jrn,t-1}$ ($\delta_{imnt} = (\log) \sum_{j \in N(i\text{'s } target)} w_{ijr,t-1} \mathbf{1}[\widehat{target}]_{jrn,t-1}$).

Table 7 column 1 presents estimates of our baseline specification using these new measures of $d_{imn,t-1}$ and $\delta_{imn,t-1}$, where neighboring firms are weighted by their eigenvector centrality in the global M&A network. Because the cross-border M&A network is sparse, the computed eigenvector centrality values for a number of relatively inactive firms can be very small, which inherently affects the values of $d_{imn,t-1}$ and $\delta_{imn,t-1}$. To avoid this scaling problem, we perform the regressions with standardized values of $d_{imn,t-1}$ and $\delta_{imn,t-1}$, and report beta (i.e., standardized) coefficients in Table 7. We leave the regression results with non-standardized values in Appendix Table A.4 for comparison. Note that the statistical significance of the estimates with non-standardized values are identical to Table 7. Column 1 shows robust evidence of the neighborhood learning effect after accounting for the heterogeneous influence of neighboring firms by their overseas investment experience. The effects of $d_{imn,t-1}$ ($\delta_{imn,t-1}$) in Panel A (B) are again shown to be statistically significant.[27]

As before, this heterogeneity can be examined further by separating firms in the spatial network into different groups. Therefore, we rank firms annually by their eigenvector centrality, and use the annual median to split the sample between more and less central firms. Comparing the coefficient magnitudes and statistical significance in column 2 to column 1, we find that the neighborhood learning effect can largely be accounted for by the presence of central firms within the spatial network. Firms that are more central have more experience, especially in important destinations, and knowledge spillovers from this group have the greatest impact. In contrast, firms that are less central have few investments abroad, and not much is gained by

[27]Similar qualitative results are obtained when firms are weighted by their degree centrality. However, because degree centrality only measures the number of links and not their quality, there is much less variation in these weights and they are less informative. These results are available upon request.

Table 7: Centrality of Neighbors and Size of Spatial Network

| | Panel A: Neighboring acquirers | | | | | |
|---|---|---|---|---|---|---|
| Spatial network radius | 0-100km | 0-100km | 0-100km | 100-200km | 200-300km | 300-400km |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $d_{imn,t-1}$ ($w_{ijr,t-1}$ = eigenvector centrality) | 0.0024*** | | | | | |
| | (4.68) | | | | | |
| $d_{imn,t-1}$ (more central) | | 0.0022*** | | | | |
| | | (3.91) | | | | |
| $d_{imn,t-1}$ (less central) | | 0.0006 | | | | |
| | | (1.10) | | | | |
| $d_{imn,t-1}$ (same sector) | | | 0.0020*** | 0.0008* | 0.0011*** | 0.0007* |
| | | | (4.28) | (1.80) | (2.97) | (1.70) |
| $d_{imn,t-1}$ (different sector) | | | 0.0011** | 0.00003 | -0.0005 | 0.0003 |
| | | | (2.21) | (0.08) | (-1.33) | (0.60) |
| Controls | Y | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 |

| | Panel B: Neighboring targets | | | | | |
|---|---|---|---|---|---|---|
| Spatial network radius | 0-100km | 0-100km | 0-100km | 100-200km | 200-300km | 300-400km |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta_{imn,t-1}$ ($w_{ijr,t-1}$ = eigenvector centrality) | 0.0012** | | | | | |
| | (2.52) | | | | | |
| $\delta_{imn,t-1}$ (more central) | | 0.0012** | | | | |
| | | (2.52) | | | | |
| $\delta_{imn,t-1}$ (less central) | | -0.0001 | | | | |
| | | (-0.45) | | | | |
| $\delta_{imn,t-1}$ (same sector) | | | 0.0008** | 0.0007* | 0.0008** | 0.0005 |
| | | | (2.03) | (1.75) | (2.05) | (1.23) |
| $\delta_{imn,t-1}$ (different sector) | | | 0.0008* | -0.0005 | 0.0003 | 0.0004 |
| | | | (1.76) | (-1.30) | (0.69) | (0.93) |
| Controls | Y | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. All regressions are estimated with OLS, and include controls for GDP, Distance, Land border, Legal, Language, Colonial ties, FTA, (log) Locations$_{imr,t-1}$, (log) $A_{-mnt}$, (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$, (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t_0}$, firm, destination, and year fixed effects. Standardized coefficients are shown. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

interacting with them. Additional information from SDC Platinum also reveals that network centrality is correlated with other firm characteristics. While data for sales, total assets, and employment is provided only for around half of the acquirers (and an even smaller percentage of targets), the average sales, total assets, and number of employees are all roughly 5 times larger for firms above the median compared to below. Thus, not only are the more central companies are larger, they presumably have more expansive domestic networks as well.

In the remaining columns of Table 7, we explore the sensitivity of our results with respect to the spatial proximity of neighbors, and continue to weight neighbors by their eigenvector centrality measures to capture their experience. We vary the distance of the neighborhood by increments of 100km up to 400km, and show that the influence of firms at farther distances is explained by the connections of companies within sectors. The positive impact of firms in the same sector is observed until 400km for neighboring acquirers in Panel A, and the effect disappears for neighboring targets only at 400km. According to Appendix Table A.5, which reports the largest distance between locations within state borders for all 50 US states, this is approximately half of the average width of a state (582km). Meanwhile, in unreported results, we find without differentiating the sector of firms, spatial networks do not have any influence beyond 100km. Thus, along with the results from column 2, this suggests that the geographic diffusion of knowledge is limited by spatial networks, but not the networks created through connections in industry.

#### 5.2.4 Accumulated experience

Finally, we explore the role of firms' accumulated experience at the micro level by introducing measures of accumulated experience $D_{imn,t-1} = (\log) \sum_{s=0}^{t-1} \sum_r W_{rn,t-1} \mathbf{1}[\widehat{acquirer}]_{imrs}$ into the regression equation. In the macro-level regression, we began by applying equal weights to $W_{rn,t-1}$. However, because the dependent variable for the micro-level estimating equation is simply an indicator variable for destination choice, the lack of variation across destinations with equal weights would not be meaningful. Therefore, in Table 8, we utilize the same weights for the closeness of (non-US) third country $r$ to destination $n$ from Table 3 columns 2 to 6. These are the inverse of the distance between $r$ and $n$, the aggregate number of acquisitions from $r$ to $n$ last year $A_{rn,t-1}$, aggregate sales $A_{nr,t-1}$, as well as combinations that summarize the two measures of closeness.

To test Proposition 5, we begin by examining the impact of firms' global experience solely in Table 8 Panel A. As in the macro regressions, the micro-level weighted sum of acquisitions also has an impact on the extensive margin of the firm. The coefficients on $D_{imn,t-1}$ are all positive and statistically significant (at the 1% level). Although we are unable to identify the source of learning in these non-US third countries, the evidence of Table 8 shows that previous experience in other non-US third countries that are geographically closer and more economically integrated with the destination of interest has an strong impact on the current destination choice. For example, in column 1, holding the number of acquisitions in third countries fixed, a 10% decrease in distance between all third countries $r$ and destination $n$ increases the probability of entry by around 0.05 percentage points ($0.1 \times 0.0047$). If, for simplicity, we take firms' entry decisions to be independent, then the orders of magnitude for the estimates of Panel A are roughly consistent with the macro-level regression results from Section 5.1. Comparing columns 2 and 3 against columns 4 and 5, we also find a larger impact of experience in third countries with more purchases in the destination as opposed to sales.

Next, in Panels B and and C, we jointly study the learning effects from accumulated experience and the local knowledge spillovers in the third country of the US. Neighboring firms are weighted equally, as in Table 4, to facilitate comparisons with the baseline results. Even after controlling for acquirers' history of investments abroad, the impact of the third-country neighborhood learning effect remains.

Lastly, in Table 9, we interact firms' micro-level signals in the US with their accumulated

Table 8: Impact of Accumulated Investment Experience

| | Panel A: Accumulated experience | | | | |
|---|---|---|---|---|---|
| Weight $W_{rn,t-1}$: | $\frac{1}{Distance_{rn}}$ | $A_{rn,t-1}$ | $\frac{A_{rn,t-1}}{Distance_{rn}}$ | $A_{nr,t-1}$ | $\frac{A_{nr,t-1}}{Distance_{rn}}$ |
| | (1) | (2) | (3) | (4) | (5) |
| $D_{imn,t-1} = (\log) \sum_{s=0}^{t-1} \sum_r W_{rn,t-1} \mathbf{1}[\widehat{acquirer}]_{imrs}$ | 0.0047*** | 0.0063*** | 0.0055*** | 0.0031*** | 0.0031*** |
| | (13.33) | (22.51) | (17.32) | (20.18) | (18.12) |
| Controls | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.045 | 0.045 | 0.045 | 0.045 |

| | Panel B: With neighboring acquirers | | | | |
|---|---|---|---|---|---|
| Weight $W_{rn,t-1}$: | $\frac{1}{Distance_{rn}}$ | $A_{rn,t-1}$ | $\frac{A_{rn,t-1}}{Distance_{rn}}$ | $A_{nr,t-1}$ | $\frac{A_{nr,t-1}}{Distance_{rn}}$ |
| | (1) | (2) | (3) | (4) | (5) |
| $d_{imn,t-1} = (\log) \sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t-1}$ | 0.0041*** | 0.0033*** | 0.0038*** | 0.0036*** | 0.0038*** |
| | (7.43) | (5.90) | (6.82) | (6.52) | (6.91) |
| $D_{imn,t-1}$ | 0.0046*** | 0.0061*** | 0.0054*** | 0.0030*** | 0.0030*** |
| | (13.22) | (21.83) | (16.99) | (19.60) | (17.80) |
| Controls | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.045 | 0.045 | 0.045 | 0.045 |

| | Panel C: With neighboring targets | | | | |
|---|---|---|---|---|---|
| Weight $W_{rn,t-1}$: | $\frac{1}{Distance_{rn}}$ | $A_{rn,t-1}$ | $\frac{A_{rn,t-1}}{Distance_{rn}}$ | $A_{nr,t-1}$ | $\frac{A_{nr,t-1}}{Distance_{rn}}$ |
| | (1) | (2) | (3) | (4) | (5) |
| $\delta_{imn,t-1} = (\log) \sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t-1}$ | 0.0031*** | 0.0026*** | 0.0018** | 0.0028*** | 0.0022** |
| | (3.58) | (2.93) | (2.08) | (3.19) | (2.52) |
| $D_{imn,t-1}$ | 0.0046*** | 0.0062*** | 0.0054*** | 0.0030*** | 0.0030*** |
| | (13.27) | (22.28) | (16.89) | (20.00) | (17.75) |
| Controls | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.045 | 0.045 | 0.045 | 0.045 |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. All regressions are estimated with OLS, and include controls for GDP, Distance, Land border, Legal, Language, Colonial ties, FTA, (log) Locations$_{imr,t-1}$, (log) $A_{-mnt}$, (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$, and (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t_0}$. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

experience in all third countries. In both Panels A and B and across all columns, the interaction term is positive and statistically significant. This is consistent with the latter part of Proposition 5, which predicts the neighborhood learning effect to be stronger with more transactions into third countries in the past. Comparing two foreign firms with the same number of acquisitions in third countries, a one-standard-deviation increase in the (lagged) number of neighboring acquirers (targets) would raise the probability of entry by 0.09 (0.04) percentage points more for the firm that invests in third countries that are all 10% closer in distance to the destination. Together with the results of Table 5, the evidence indicates that, regardless of the knowledge source, the information obtained through the various channels have complementary effects on the acquirer firm's choice of destination market.

Table 9: Intensity of Neighborhood Learning Effect with Accumulated Experience

| | Panel A: Interaction with neighboring acquirers | | | | |
|---|---|---|---|---|---|
| Weight $W_{rn,t-1}$: | $\frac{1}{Distance_{rn}}$ | $A_{rn,t-1}$ | $\frac{A_{rn,t-1}}{Distance_{rn}}$ | $A_{nr,t-1}$ | $\frac{A_{nr,t-1}}{Distance_{rn}}$ |
| | (1) | (2) | (3) | (4) | (5) |
| $d_{imn,t-1}$ | 0.0225*** | -0.0013* | 0.0016*** | 0.0142*** | 0.0118*** |
| | (10.52) | (-1.90) | (2.63) | (9.59) | (7.16) |
| $D_{imn,t-1}$ | 0.0031*** | 0.0038*** | 0.0039*** | 0.0018*** | 0.0021*** |
| | (8.76) | (11.27) | (10.15) | (10.22) | (10.55) |
| $d_{imn,t-1} \times D_{imn,t-1}$ | 0.0025*** | 0.0025*** | 0.0015*** | 0.0015*** | 0.0011*** |
| | (9.20) | (8.14) | (4.80) | (8.36) | (5.56) |
| Controls | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.045 | 0.046 | 0.045 | 0.046 | 0.045 |
| | Panel B: Interaction with neighboring targets | | | | |
| Weight $W_{rn,t-1}$: | $\frac{1}{Distance_{rn}}$ | $A_{rn,t-1}$ | $\frac{A_{rn,t-1}}{Distance_{rn}}$ | $A_{nr,t-1}$ | $\frac{A_{nr,t-1}}{Distance_{rn}}$ |
| | (1) | (2) | (3) | (4) | (5) |
| $\delta_{imn,t-1}$ | 0.0157*** | -0.0013 | 0.0004 | 0.0105*** | 0.0063*** |
| | (5.02) | (-1.20) | (0.38) | (5.05) | (2.97) |
| $D_{imn,t-1}$ | 0.0040*** | 0.0053*** | 0.0050*** | 0.0025*** | 0.0027*** |
| | (11.47) | (16.89) | (13.49) | (15.37) | (14.05) |
| $\delta_{imn,t-1} \times D_{imn,t-1}$ | 0.0018*** | 0.0018*** | 0.0007 | 0.0012*** | 0.0006** |
| | (4.38) | (4.13) | (1.54) | (4.59) | (2.37) |
| Controls | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.045 | 0.045 | 0.045 | 0.045 |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. All regressions are estimated with OLS, and include controls for GDP, Distance, Land border, Legal, Language, Colonial ties, FTA, (log) $\text{Locations}_{imr,t-1}$, (log) $A_{-mnt}$, (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$, and (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t_0}$. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

# 6 Conclusion

In this paper, we propose local knowledge spillovers within spatial networks in prior destinations as a channel through which firms learn about their destination of interest. Thus, acquirers obtain knowledge on new destinations through their targets in third countries. We present a heterogeneous-firm model of cross-border M&A that provides a micro-foundation for learning in third countries, either through multinationals' accumulated experience, or through the networks of their third-country targets.

Using data on global cross-border M&A activity from 1995 to 2016, we find strong empirical support for the model at both the aggregate and micro levels. The number of acquisitions to a destination is increasing in the number of prior acquisitions to third countries that are closer to that market. At the micro level, we test our hypotheses by examining foreign acquirers in the US, and the spatial networks of their targets. We find that the number of acquisitions, as well as sales, by the neighboring firms of the US target has a positive impact on the destination choice of the non-US acquirer. The third-country neighborhood learning effects are found to be stronger for firms in the same state, same sector, and in downstream (as opposed to upstream) sectors.

In addition, using eigenvector centrality, we show that the learning effect increases with the centrality of neighbors. Furthermore, prior experience in third countries that are geographically closer to or more integrated with the destination of interest also raises the chance of investing in that destination. These learning effects are complementary across the various information sources of the firm.

Economic markets are generally more efficient in the US compared to other countries, which implies greater knowledge spillovers and less information frictions. A comparison of the learning effects between the US and other countries may improve our understanding of the role of information frictions and measures to mitigate them. We leave this for future research.

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# A Appendix

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) | Agricultural products | 68848 | 59 | 4763 | 145862 | 110 | 1347 | 9342 | 9492 | 459 |
| (2) | Minerals | 356 | 30369 | 6437 | 117806 | 59985 | 33 | 5 | 30 | 2524 |
| (3) | Construction | 3172 | 3520 | 762 | 24625 | 40330 | 10565 | 66794 | 24827 | 22713 |
| (4) | Manufacturing products | 49451 | 13724 | 263333 | 1316232 | 71106 | 67694 | 19028 | 300918 | 16216 |
| (5) | Transportation, communication, utilities | 11990 | 12606 | 22406 | 167996 | 181266 | 60754 | 47215 | 105833 | 19144 |
| (6) | Trade | 14596 | 3514 | 72895 | 228714 | 18377 | 31025 | 4829 | 62596 | 2627 |
| (7) | Finance | 20743 | 23612 | 14399 | 62418 | 35421 | 94817 | 325189 | 208315 | 6508 |
| (8) | Services | 7765 | 5373 | 83664 | 217092 | 123075 | 182012 | 155782 | 429178 | 10104 |
| (9) | Other | 156 | 29 | 908 | 12827 | 2854 | 9393 | 20582 | 20537 | 1586 |

Figure A.1: Input output matrix for the US in 1996. For each row, upstream sectors are indicated with a solid border. For each column, downstream sectors are shaded.

Table A.1: Top 20 Origin and Destination Countries

| | Origin country | Acquisitions made | Percentage | Destination country | Targets sold | Percentage |
|---|---|---|---|---|---|---|
| 1 | United States | 38,756 | 20.6 | United States | 24,499 | 13.0 |
| 2 | United Kingdom | 18,503 | 9.83 | United Kingdom | 15,074 | 8.01 |
| 3 | Canada | 13,498 | 7.17 | Germany | 11,348 | 6.03 |
| 4 | Germany | 10,162 | 5.40 | China | 9826 | 5.22 |
| 5 | France | 9292 | 4.94 | Canada | 9020 | 4.79 |
| 6 | Hong Kong | 7859 | 4.18 | France | 7628 | 4.05 |
| 7 | Netherlands | 7044 | 3.74 | Australia | 7097 | 3.77 |
| 8 | Japan | 5911 | 3.14 | India | 4872 | 2.59 |
| 9 | Singapore | 5647 | 3.00 | Italy | 4586 | 2.44 |
| 10 | Australia | 5531 | 2.94 | Spain | 4546 | 2.42 |
| 11 | Sweden | 5455 | 2.90 | Netherlands | 4520 | 2.40 |
| 12 | Switzerland | 5149 | 2.74 | Hong Kong | 4073 | 2.16 |
| 13 | China | 3729 | 1.98 | Russia | 3979 | 2.11 |
| 14 | Spain | 2994 | 1.59 | Sweden | 3955 | 2.10 |
| 15 | Italy | 2883 | 1.53 | Brazil | 3563 | 1.89 |
| 16 | Belgium | 2727 | 1.45 | Switzerland | 3110 | 1.65 |
| 17 | Malaysia | 2467 | 1.31 | Singapore | 2793 | 1.48 |
| 18 | Denmark | 2357 | 1.25 | Norway | 2630 | 1.40 |
| 19 | Cyprus | 2335 | 1.24 | Belgium | 2551 | 1.36 |
| 20 | Norway | 2320 | 1.23 | Poland | 2496 | 1.33 |

*Notes:* Authors' calculations using cross-border M&A data between 1995 and 2016 from Thomson Reuters SDC Platinum.

Table A.2: Top 20 Cities for Acquisitions and Sales Transactions

| | Acquirer city | Acquirer state | Acquisitions made | Target city | Target state | Targets sold |
|---|---|---|---|---|---|---|
| 1 | New York | New York | 1615 | New York | New York | 1090 |
| 2 | Houston | Texas | 469 | Houston | Texas | 520 |
| 3 | Chicago | Illinois | 288 | San Francisco | California | 376 |
| 4 | San Francisco | California | 286 | Chicago | Illinois | 330 |
| 5 | Los Angeles | California | 231 | Los Angeles | California | 308 |
| 6 | Boston | Massachusetts | 215 | San Diego | California | 257 |
| 7 | Dallas | Texas | 215 | Dallas | Texas | 216 |
| 8 | Atlanta | Georgia | 207 | Atlanta | Georgia | 201 |
| 9 | Las Vegas | Nevada | 159 | Boston | Massachusetts | 193 |
| 10 | San Diego | California | 147 | San Jose | California | 190 |
| 11 | Denver | Colorado | 139 | Seattle | Washington | 186 |
| 12 | San Jose | California | 130 | Miami | Florida | 169 |
| 13 | Seattle | Washington | 126 | Denver | Colorado | 138 |
| 14 | Miami | Florida | 122 | Santa Clara | California | 133 |
| 15 | Salt Lake City | Utah | 114 | Irvine | California | 132 |
| 16 | Washington | D.C. | 113 | Austin | Texas | 130 |
| 17 | Stamford | Connecticut | 106 | Washington | D.C. | 119 |
| 18 | Minneapolis | Minnesota | 103 | Minneapolis | Minnesota | 119 |
| 19 | Irvine | California | 100 | Las Vegas | Nevada | 110 |
| 20 | Austin | Texas | 93 | Sunnyvale | California | 109 |

*Notes:* Authors' calculations using cross-border M&A data for the US between 1995 and 2016 from Thomson Reuters SDC Platinum.

Table A.3: Instrumental Variables Regression, First Stage

| Neighboring | Acquirers | Targets |
|---|---|---|
| Dependent variable | $d_{imn,t-1}$ | $\delta_{imn,t-1}$ |
| | (1) | (2) |
| (log) $\text{Pop}^g_{mr}$ × (log) $\text{Pop}^g_{nr}$ | 0.0032*** | 0.0011*** |
| | (36.14) | (22.78) |
| (log) $\text{Locations}_{imr,t-1}$ | 0.0940*** | 0.0222*** |
| | (12.45) | (7.28) |
| (log) $A_{-mnt}$ | 0.0613*** | 0.0068*** |
| | (35.86) | (8.08) |
| (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$ | 0.3777*** | 0.1575*** |
| | (88.94) | (66.69) |
| (log) $\sum_{j\in N(i\text{'s } target)} \mathbf{1}[\widehat{target}]_{jrn,t_0}$ | 0.2736*** | 0.4027*** |
| | (73.54) | (77.15) |
| Controls: | GDP, Distance, Land border<br>Legal, Language, Colonial ties, FTA | |
| Firm, Destination, and Year FE | Y | Y |
| N | 496,076 | 496,076 |

*Notes:* Column 1 (2) shows estimates for the first-stage regression of Table 4 Panel A (B) column 6. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Table A.4: Centrality of Neighbors and Size of Spatial Network, Unstandardized Coefficients

| | Panel A: Neighboring acquirers | | | | | |
|---|---|---|---|---|---|---|
| Spatial network radius | 0-100km | 0-100km | 0-100km | 100-200km | 200-300km | 300-400km |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $d_{imn,t-1}$ ($w_{ijr,t-1}$ = eigenvector centrality) | 0.0458*** | | | | | |
| | (4.68) | | | | | |
| $d_{imn,t-1}$ (more central) | | 0.0412*** | | | | |
| | | (3.91) | | | | |
| $d_{imn,t-1}$ (less central) | | 0.3625 | | | | |
| | | (1.10) | | | | |
| $d_{imn,t-1}$ (same sector) | | | 0.0815*** | 0.0623* | 0.0983*** | 0.0488* |
| | | | (4.28) | (1.80) | (2.97) | (1.70) |
| $d_{imn,t-1}$ (different sector) | | | 0.0261** | 0.0016 | -0.0264 | 0.0099 |
| | | | (2.21) | (0.08) | (-1.33) | (0.60) |
| Controls | Y | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 |
| | Panel B: Neighboring targets | | | | | |
| Spatial network radius | 0-100km | 0-100km | 0-100km | 100-200km | 200-300km | 300-400km |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | (1.76) | (-1.30) | (0.69) | (0.93) |
| $\delta_{imn,t-1}$ ($w_{ijr,t-1}$ = eigenvector centrality) | 0.6640** | | | | | |
| | (2.52) | | | | | |
| $\delta_{imn,t-1}$ (more central) | | 0.6642** | | | | |
| | | (2.52) | | | | |
| $\delta_{imn,t-1}$ (less central) | | -103.2002 | | | | |
| | | (-0.45) | | | | |
| $\delta_{imn,t-1}$ (same sector) | | | 0.9225** | 1.0777* | 0.0044*** | 0.8694 |
| | | | (2.03) | (1.75) | (5.09) | (1.23) |
| $\delta_{imn,t-1}$ (different sector) | | | 0.5664* | -0.5352 | 0.0031** | 0.3711 |
| | | | (1.76) | (-1.30) | (2.31) | (0.93) |
| Controls | Y | Y | Y | Y | Y | Y |
| Firm, Destination, and Year FE | Y | Y | Y | Y | Y | Y |
| N | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 | 496,076 |
| $R^2$ | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 |

*Notes:* The dependent variable is an indicator variable for acquisition in $n$ by firm $i$ at time $t$. All regressions are estimated with OLS, and include controls for GDP, Distance, Land border, Legal, Language, Colonial ties, FTA, (log) Locations$_{imr,t-1}$, (log) $A_{-mnt}$, (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{acquirer}]_{jrn,t_0}$, (log) $\sum_{j \in N(i\text{'s target})} \mathbf{1}[\widehat{target}]_{jrn,t_0}$, firm, destination, and year fixed effects. $T$-statistics are in parentheses, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Table A.5: Largest Distance between Locations within States

| Rank | State | Distance (km) | Rank | State | Distance (km) |
|---|---|---|---|---|---|
| 1 | Alaska | 2044 | 26 | Kentucky | 561 |
| 2 | Texas | 1208 | 27 | Missouri | 558 |
| 3 | California | 1188 | 28 | Alabama | 549 |
| 4 | Florida | 873 | 29 | Utah | 548 |
| 5 | Montana | 848 | 30 | Illinois | 531 |
| 6 | Idaho | 787 | 31 | Wisconsin | 528 |
| 7 | Nevada | 745 | 32 | Mississippi | 514 |
| 8 | Michigan | 740 | 33 | Washington | 512 |
| 9 | Tennessee | 716 | 34 | Hawaii | 506 |
| 10 | North Carolina | 657 | 35 | Iowa | 498 |
| 11 | Kansas | 653 | 36 | Pennsylvania | 492 |
| 12 | Oklahoma | 645 | 37 | Maine | 490 |
| 13 | Wyoming | 644 | 38 | Indiana | 472 |
| 14 | New Mexico | 637 | 39 | Ohio | 445 |
| 15 | Nebraska | 636 | 40 | Arkansas | 435 |
| 16 | South Dakota | 632 | 41 | West Virginia | 400 |
| 17 | New York | 616 | 42 | South Carolina | 389 |
| 18 | Virginia | 615 | 43 | Maryland | 336 |
| 19 | Arizona | 610 | 44 | Massachusetts | 304 |
| 20 | Oregon | 606 | 45 | Vermont | 236 |
| 21 | Minnesota | 597 | 46 | New Jersey | 211 |
| 22 | Colorado | 593 | 47 | New Hampshire | 197 |
| 23 | Georgia | 586 | 48 | Connecticut | 183 |
| 24 | Louisiana | 585 | 49 | Delaware | 130 |
| 25 | North Dakota | 566 | 50 | Rhode Island | 73 |
| Average (standard deviation) | | | | | 582 (304) |
| Average (standard deviation) excluding Alaska and Hawaii | | | | | 554 (224) |

*Notes:* Author's calculations for largest driving distance between 4,706 locations with cross-border M&A activity.