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Evidence for the effect of monitoring costs on foreign direct investment

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ABSTRACT

A proposed reason for the significant inverse relationship between distance (both physical and cultural) and foreign direct investment is the increased costs for a parent firm to monitor an affiliate when there is greater distance between them. We provide the first direct test of this hypothesis using O*NET data on occupational skills to construct industry-level measures of the importance of monitoring-related skills. We exploit this cross-industry variation to examine whether physical and cultural distances have a greater impact on cross-border M&A in industries where monitoring-related skills are more important. Using data on worldwide cross-border M&A activity from 2005 through 2014, we find significant evidence for the effect of monitoring costs on cross-border M&A activity. We also show that the relatively low importance of monitoring-related costs in manufacturing industries compared to those in other sectors is an important factor in explaining why cross-border M&A in manufacturing is so large despite its relatively small share in most countries.

1. Introduction

The growth of world foreign direct investment (FDI) over the past few decades has been rapid. In accordance with this, there has been a significant research effort to explore the determinants (and frictions) that shape worldwide FDI patterns. As with international trade and other international transactions, gravity variables are significant explanatory variables for bilateral FDI flows and stocks. While it makes sense that country size measures should be positively correlated with respect to any international transaction one considers, the source of the inverse correlation with distance is less obvious. The common explanation for the inverse correlation between distance and international trade is transport costs. But this is an unlikely explanation for the inverse correlation of distance with FDI unless most firms engaging in FDI intend to trade a significant amount of inputs between the parent and its foreign affiliates. Also, most empirical studies of trade and FDI patterns include cultural distance measures such as language similarity, colonial relationships, etc., finding they are also significant frictions for these international transactions.

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A common explanation for the inverse correlation between FDI and physical and cultural distances is that they negatively affect the ease and efficiency of communication, coordination, and monitoring of activity across the firm's affiliates. Greater distance makes the prospect of FDI less profitable and therefore less likely. Head and Ries (2008) provide a theoretical model based on these principles for cross-border M&A (a major type of FDI). They derive a gravity-like equation for explaining bilateral cross-country M&A flows that predicts inverse relationships with physical and cultural distances due to the increased costs for the parent firm to monitor its foreign affiliate as these distances increase.

While this hypothesis for the inverse relationship between FDI and physical and cultural distance is intuitive, there is no direct evidence of which we are aware that monitoring costs are the source of these relationships. And there are other plausible reasons for these relationships besides monitoring costs. Physical distances are often associated with transport costs in the international trade literature, and so the evidence for the significance of physical distance could be because transport of intermediates between the parent and affiliate are substantial and costly with increased distance, not because monitoring is challenged by distance. Likewise, there are a number of reasons for why cultural distances might be deleterious to cross-border M&A other than monitoring costs. For example, their main impact may be in making it difficult to find appropriate targets in a potential host country, not monitoring it once they have acquired a target. Understanding the mechanisms behind the inverse correlation between FDI and distance is thus vital for refining our knowledge of FDI and our ultimate ability to inform policy.

Besides Head and Ries (2008), other prior empirical analyses have also argued that monitoring and communication costs are important for FDI and are the mechanism behind a number of empirical relationships. These include several papers that find evidence that cross-country institutional and legal differences hinder FDI (e.g., Habib and Zurawicki (2002), Aizenmann and Spiegel (2006), Bénassy-Quéré et al. (2007), and Raimondi and Scoppola (2018)) and a paper by Stein and Daude (2007) finding that FDI is more prevalent in countries in the same (or proximate) time zones because it is easier to communicate during common business hours.[1] Like Head and Ries (2008), these studies rely on cross-country differences for evidence consistent with their hypotheses. This approach suffers from the critique that other unobserved country-level differences may be driving these correlations which are otherwise unrelated to the postulated mechanism.

In contrast, this paper uses an identification method analogous to that of Rajan and Zingales (1998) to provide the first direct test of the monitoring-cost hypothesis. We develop a new cross-industry measure of the importance of monitoring and related skills for firms within industrial sectors and interact this sectoral data with cross-country measures of physical and cultural distances. If these bilateral country distances are hampering FDI due to monitoring costs, then we should see that they are especially harmful to industrial sectors where monitoring is more important.

In order to implement this identification strategy within a theoretical framework, we extend the Head and Ries (2008) model of cross-border M&A activity to incorporate sectoral heterogeneity, as their original model is only specified at the country level. We then use cross-border M&A data from the Thomson SDC Platinum database ranging from 2005 to 2014 as our measure of FDI. There are two main reasons for this. First, the value of cross-border M&A activity is typically double that of greenfield FDI, the other major form of FDI. (For example, see Table I.10 on p. 11 of UNCTAD, 2015). Thus, by conducting the empirical analysis with cross-border M&A data, we are capturing a substantial portion of the worldwide FDI activity. Second, the cross-border M&A data from the SDC Platinum database provides disaggregated information across all countries at the four-digit SIC level – a level of detail that other FDI data cannot provide even for the countries with the most comprehensive FDI data.

We use data from the Occupational Information Network (O*NET) of the U.S. Department of Labor to measure the extent to which occupations require various skills and construct a measure of how important monitoring is in an industry.[2] While the previous literature has used these data primarily to look at the routineness of tasks that workers may be asked to do, the dataset also contains information on the degree to which various occupations require such things as monitoring of others, interpersonal skills, and communication skills. These directly connect to the Head and Ries (2008) rationale for why physical and cultural distances are inversely correlated with FDI. Using data on the employment shares of occupations for each industry (available from the Bureau of Labor Statistics), we construct measures of the importance of these monitoring-related skills by industry and interact them with the measures of physical and cultural distance between bilateral country pairs so that we can examine whether there is direct causal evidence for the monitoring cost mechanism.

Our econometric results provide strong evidence in favor of monitoring costs as a source of reduced cross-border M&A activity. We find that a standard deviation increase in the monitoring importance in an industry is associated with a decrease in M&A activity of about 36% for our main sample and specification and this effect is statistically significant at the 1% level. These results are robust to a number of alternative samples and specifications, including alternative measures of monitoring importance and different samples of countries and years.

With our establishment that monitoring costs are an important mechanism driving the negative impact of physical and cultural distances on cross-border M&A, we use our estimates to investigate whether these costs are also significant in

[1] These papers are part of a growing literature that investigates the determinants of cross-border M&A, including Rossi and Volpin (2004), Di Giovanni (2005) Head and Ries (2008), Hijzen et al. (2008), Erel et al. (2012), and Blonigen and Piger (2014). These studies generally find that gravity-type forces are important for cross-border M&A and especially examine the role of various types of cross-border frictions, as well as financial and institutional frictions in the home and host country.

[2] These data are available online at: https://www.onetonline.org. We use O*NET's ranking of the relevance and level of various social skills which we explain further below.

explaining another important feature of cross-border M&A activity – a substantial share of global FDI is in manufacturing and undertaken primarily amongst developed countries, yet manufacturing accounts for a very small (and rapidly declining) share of activity in these same developed countries.[3] Could it be that the disproportionately larger share of cross-border M&A in manufacturing is because there is less monitoring of affiliates required in manufacturing than other sectors? The raw data are consistent with this hypothesis, as our constructed measures of the importance of monitoring-related skills for the wholesale, retail, and financial, insurance, and real estate sectors (FIRE) are three to four times larger than for the manufacturing sector. We also find strong evidence for this when applying our formal econometric analysis. On average, our estimates suggest that cross-border M&A activity would be more than 50% higher in the non-manufacturing sectors if they required as little monitoring-related skills as in manufacturing. However, there is significant heterogeneity across the non-manufacturing sectors. If monitoring importance were as low as that required in manufacturing, the high-monitoring sectors of wholesale trade, retail trade, and finance, insurance, and real estate would see their cross-border M&A activity more than double according to our estimates. But there would be much smaller increases (between 3 and 20%) in the services, construction, and transportation, communications, and utilities sectors.[4]

There are other papers that have used a similar strategy of interacting industry characteristics with cross-country differences to correlate it with FDI activity. Keller and Yeaple (2013) show that affiliates are more likely to import inputs from their parent firms when an industry is knowledge-intensive because it is easier to imbed the knowledge in imported inputs than to communicate the knowledge in disembodied form to the affiliate. A consequence, which they confirm empirically, is that cross-country distances and other trade frictions will be associated with lower FDI and affiliate sales in more knowledge-intensive industries.[5] Relatedly, Bahar (2018) finds that this knowledge-intensity and distance tradeoff is weakened when communication costs between the affiliate and parent are reduced by having a greater overlap in business hours (i.e., the same or proximate time zones).

A potential concern is whether our monitoring intensity effect is different from and/or identifiable from the knowledge-intensity effect in Keller and Yeaple (2013) and Bahar (2018). First, we note that there is a theoretical difference because sectors requiring substantial monitoring need not be ones that are knowledge-intensive. For example, our data indicate that retail establishments require substantial monitoring, but these are not sectors where the "production process" would be considered knowledge-intensive. Second, after presenting our main results, we show our results are highly robust to including interactions of a number of knowledge-intensity measures.[6]

The rest of the paper proceeds as follows. Sections 2 and 3 describe our O*NET measure of monitoring across industrial sectors and our data on cross-border M&A activity, respectively. Section 4 derives an empirical specification from the Head and Ries (2008) model and describes our identification strategy. Section 5 provides our empirical results both for the evidence on the monitoring-cost effect on FDI and how much it explains the heterogeneous cross-border M&A activity we see across industrial sectors. The final section concludes.

2. Occupational data on monitoring-related skills

A novel aspect of our analysis compared to the previous literature is the use of information from the Occupational Information Network (O*NET) dataset in order to measure the skills that are likely connected with parent firms' monitoring of foreign affiliates and whose use may be made more difficult by greater physical and/or cultural distance. O*NET ranks both the level and the importance of over a hundred various skills for over 950 different occupations in the United States. We gather "monitoring skills" from O*NET that include four skills that are labeled, "Coordination," "Management of material resources," "Management of personnel," and "Monitoring." These are tasks that likely become more difficult as the affiliate becomes more remote from the parent, irrespective of any cultural or language differences. Head and Ries (2008) posit that cultural distance can affect monitoring and use proxies such as language differences and colonial relationships for the cultural distance that will affect monitoring costs. Following this, we also group a number of these O*NET social skills into categories we label "cultural skills" and "language skills." The cultural skills we consider are those labeled by O*NET as "Negotiation skills," "Persuasion," "Service orientation," and "Social perceptiveness." Language skills include those labeled by O*NET as "Active listening," "Instructing," "Reading comprehension," "Speaking," and "Writing." Appendix B provides the O*NET description of each of these thirteen skills across the three categories of monitoring skills, cultural skills and language skills, respectively.

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[3] For example, in the US, over 45% of value added by foreign affiliates operating in the US was in manufacturing in 2012 (Calculated from Table 2.1 in Anderson 2014). However, total value added by manufacturing sector in the US accounted for only about 12% of real GDP in 2012 (Elrod et al., 2013, Table E). Likewise, almost 40% of value added in 2011 by US affiliates operating in foreign countries was in manufacturing (Calculated from Table 2.1 in Barefoot, 2013).

[4] Most prior FDI studies only examine data on manufacturing industries. Exceptions include Feliciano and Sun (2016), Kleinert and Toubal (2013), and Krautheim (2013), though none have examined the issues we focus on.

[5] Oldenski (2012) finds that export to FDI ratios to foreign markets are higher for sectors that involve more complex, non-routine tasks, but the paper doesn't explore the interaction of this with physical distance and other cross-country frictions.

[6] A related paper by Davies et al. (2018) hypothesizes that cross-border M&A should be more frequent relative to greenfield when integration of the acquired target would be more difficult. They interact sectoral measures of input contractability and intangible assets with physical and cultural differences and find evidence that cross-border M&A is affected more than greenfield FDI by physical and cultural distances in sectors where input contractibility and intangible assets are high. These results are about the form that FDI takes, not about total FDI activity, which is our focus.

Table 1
Summary Statistics for the O*NET Variable.

Sector	Mean	St. Dev.	Min	Max	Obs.
All Sectors	0.061	0.053	0.000	0.257	365
Manufacturing	0.033	0.015	0.000	0.096	140
Non-Manufacturing	0.078	0.061	0.002	0.257	225
Mining	0.021	0.012	0.005	0.055	17
Construction	0.037	0.017	0.021	0.090	14
Transportation, communicationsand utilities	0.039	0.034	0.004	0.201	35
Wholesale trade	0.108	0.021	0.060	0.136	18
Retail trade	0.158	0.056	0.021	0.257	41
Finance, insurance, and real estate	0.112	0.036	0.046	0.182	30
Services	0.051	0.040	0.002	0.229	70

Notes: Authors calculations. O*NET variable is a measure of the importance of monitoring, language and cultural skills needed for the composition of occupations in an industrial sector. See text for further description of the construction of the measure.

O*NET ranks the relevance of each skill for each occupation along two dimensions: importance and level. Importance (ranked from 1 to 5) measures how essential the skill is for the occupation, whereas the level (ranked from 0 to 7) indicates how proficient one must be in that skill for the occupation. These need not be highly correlated. For example, writing skills may be important for an occupation such as a parking citations officer on a daily basis, but not required to be at the highest level of proficiency.

In order to construct measures of the relevance of these thirteen skills at the industry level, we undertake the following steps. First, we multiply the level and importance of each skill for each occupation and rescale so that all values fall between 0 and 1. We then use the Occupational Employment Statistics (OES) survey provided by the Bureau of Labor Statistics (BLS) on employment by 3-digit Standard Industrial Classification (SIC) industries across Standard Occupational Codes (SOCs) for the year 2000 to determine the share of each occupation for each industry.[7] Using these shares, we create a weighted average of the relevance of each skill for each industry.

A final refinement is that we construct these measures with respect to only the occupation codes that are likely to be important for monitoring and coordinating activity between the parent and the affiliate: Management (SOC 11), Business and Financial Operations (SOC 13), and Sales and Related Occupations (SOC 41). We think it is unlikely that monitoring at non-executive levels (e.g., a floor supervisor on a production line) is important for the coordination and communication needed between a parent company and its foreign affiliate.

In practice, we find that these thirteen skills are highly correlated across 3-digit SIC industries with no pairwise correlation lower than 0.85 between any of the thirteen skills.[8] That is, industries where monitoring is important at management or executive level are also industries where language and cultural skills are important. We have tried a variety of alternative methods for constructing our skill variables that all yield very high pairwise correlations. Given this, we collapse all thirteen of our skill variables into one monitoring-related O*NET variable by taking a simple average. This simplifies our analysis in many ways and, as we show later, our results are robust to a variety of alternative ways to define and construct the O*NET variable capturing monitoring-related skills.

Table 1 provides descriptive statistics for our monitoring-related O*NET variable where higher values indicate a greater importance of monitoring-related skills. The mean value of the O*NET variable is 0.061 across our entire dataset with a standard deviation of 0.053. There is significant variation across this measure with the value of the variable ranging from a minimum of 0 to 0.257.

There is also a clear pattern in the data that monitoring-related skills are significantly less important in manufacturing industries than non-manufacturing industries. The mean value of the O*NET variable for manufacturing sectors is 0.033, which is less than half the average of non-manufacturing industries at 0.078. As seen in the final rows of Table 1, non-manufacturing industries are also quite diverse in terms of the prominence of monitoring-related skills even at the 1-digit SIC level. Monitoring-related skills are less prominent for mining than manufacturing, while retail, wholesale, and finance, insurance and real estate (FIRE) have relatively high mean values for the O*NET variable. Table 2 shows the highest ten and lowest ten 3-digit SIC industries with respect to the prominence of monitoring-related skills. The top ten industries are almost all in retail, while the lowest ten industries are in mining, transportation, and a few health and personal services. As we will see in our empirical analysis, this variation is highly significant in explaining differences in FDI patterns across countries.

[7] The U.S. Bureau of Labor Statistics (BLS) provides a crosswalk between 2010 SOC codes and 2000 SOC codes, which we use in order to merge the O*NET skills data with the occupational employment share data.

[8] The great majority of the pairwise correlation coefficients are above 0.95.

Table 2
Sectors with Highest and Lowest Importance for Monitoring-Related Skills.

Panel A: Highest Ten Sectors for Monitoring- Related Skill		
Sector	***SIC***	***O*NET Value***
Shoe Stores	566	0.257
Women's Accessory and Specialty Stores	563	0.257
Children's and Infants' Wear Stores	564	0.248
Women's Clothing Stores	562	0.246
Men's and Boys' Clothing and Accessory Stores	561	0.242
Video Tape Rental	784	0.229
Family Clothing Stores	565	0.225
Miscellaneous Shopping Goods Stores	594	0.216
Miscellaneous Apparel and Accessory Stores	569	0.216
Hardware Stores	525	0.210
Panel B: Lowest Ten Sectors for Monitoring- Related Skills		
Sector	***SIC***	***O*NET Value***
Barber Shops	724	0.002
Offices and Clinics of Dentists	802	0.004
Terminal and Service Facilities for Motor Vehicle Passenger Transportation	417	0.004
Miscellaneous Metal Ores	109	0.005
School Buses	415	0.007
Copper Ores	102	0.008
Cigars	212	0.008
Iron Ores	101	0.009
Coal Mining Services	124	0.009
Offices and Clinics of Doctors of Osteopathy	803	0.009

Notes: Authors calculations. The O*NET variable is a measure of the importance of monitoring, language and cultural skills needed for the composition of occupations in an industrial sector. See text for further description of the construction of the measure.

3. Cross-border M&A data

Like many other prior papers on M&A activity, we rely on the Thomson Reuters SDC Platinum M&A database to examine patterns in cross-border M&A activity. The database records all M&A transactions across the world that are valued at $5 million or higher. If the percentage of shares acquired by the acquiring firm is 10% or more, we consider this an acquisition. A limitation of the data is that it does not have information on the value of transactions for about half of the observations, as private firms do not have to report this information. As a result, we rely on counts of M&A transactions. The empirical model we present and estimate below naturally explains counts of transactions.

About one-quarter of the observations in the data are M&A transactions that are cross-border; i.e., the acquiring firm's headquarters are located in a different country than the target firm's headquarters. We create a dependent variable of the number of cross-border acquistions at the three-digit SIC industry level for all directional country pairs from the set of the top 50 target countries in the database and cumulate these over a ten-year period from 2005 through 2014. We limit our sample to the top 50 countries because M&A activity begins to get sparse beyond this set and then includes countries where we cannot easily obtain data for some of our regressors.[9] M&A activity between these top 50 countries accounts for over 80% of all M&A activity in the database. We also explore samples with M&A activity only across OECD countries, which have more intense M&A activity amongst them and account for a substantial share (around 60%) of overall cross-border M&A activity.[10]

We cumulate over a period of time rather than create a panel of data for a number of reasons. First, cumulation of activity over a time period reduces the number of zero observations in the data. Second, sectoral variation (how monitoring intensity varies by sector) is much more important for our identification than time series variation because our measures of cross-country frictions don't vary over time at all (physical distance) or very slowly (cultural differences). In a robustness test, we also show that our results are unchanged if we instead use a ten-year cumulation of cross-border M&A activity over the 1995–2004 period rather than the 2005–2014 period.

Importantly, the database has information on the primary 4-digit Standard Industrial Classification (SIC) industries for the acquiring and target firms, allowing us to focus on sectoral patterns of cross-border acquisitions, including non-manufacturing ones. The O*NET data are classified by the North American Industrial Classification System (NAICS) and we concord these to the 3-digit SIC level, while also aggregating our M&A data to this level.[11] For our purposes, we classify the M&A transactions according to the SIC of the target firm.

[9] We rank M&A activity in terms of the number of firms targeted in that country for M&A. Appendix A lists the countries that comprise the top 50 target countries in our full sample.

[10] We define OECD membership as of January 1, 2000. Appendix A lists the OECD countries in our sample.

[11] While many of the industries at the 3-digit SIC level have a one-to-one mapping with the NAICS, this is much less the case with the 4-digit SIC level. This creates the potential for measurement issues and is the reason we construct our data at the 3-digit SIC level.

Table 3
Sectoral Composition of Cross-border M&A.

Across Different Samples	Top 50	OECD
Manufacturing	34.4%	34.0%
Non-Manufacturing	65.6%	66.0%
Mining	7.4%	6.1%
Construction	1.6%	1.7%
Transportation, communications and utilities	8.7%	8.2%
Wholesale trade	4.9%	5.2%
Retail trade	3.0%	2.9%
Finance, insurance and real estate	12.9%	12.0%
Services	27.0%	29.9%

Notes: Authors calculations using data from Thomson Reuters SDC Platinum M&A Database, 2005–2014. Top 50 and OECD sample of countries are defined in Appendix A.

Table 4
Share of Manufacturing in Domestic and Cross-border M&A for Various Samples and Top 10 Target Countries.

	Domestic Acquisitions			**Cross-border Acquisitions**		
	Manufact-uring	*Non-Manu-facturing*	*Share of Ma-nufacturing*	*Manufact-uring*	*Non-Manu-facturing*	*Share of Ma-nufacturing*
Top 50 Sample	58,534	166,307	26.0%	20,900	39,805	34.4%
OECD Sample	43,786	133,521	24.7%	13,872	26,950	34.0%
Top 10 Target Countries		.				
Australia Targets	1195	7440	13.8%	547	1992	21.5%
Canada Targets	1421	9029	13.6%	1022	2387	30.0%
China Targets	5023	6772	42.6%	1437	1877	43.4%
France Targets	3137	6336	33.1%	1135	1454	43.8%
Germany Targets	3032	5151	37.1%	1827	2419	43.0%
Italy Targets	1223	2451	33.3%	727	772	48.5%
Netherlands Targets	745	2250	24.9%	566	1076	34.5%
Spain Targets	1575	3544	30.8%	520	1153	31.1%
UK. Targets	3144	13,532	18.9%	1587	4069	28.1%
US. Targets	16,340	53,961	23.2%	3180	5738	35.7%

Notes: Authors calculations using data from Thomson Reuters SDC Platinum M&A Database, 2005–2014. Top 50 and OECD sample of countries are defined in Appendix A.

To get a sense of the variation in cross-border M&A activity across industries, Table 3 looks at such activity across one-digit sectors for our full sample and the OECD sample. The manufacturing sector accounts for 34.4% of all cross-border M&A activity and this is nearly identical in the OECD sample. Of the non-manufacturing sectors, services is the largest and accounts for almost 30% of all cross-border M&A activity. The next largest sectors are FIRE (12–13%), transportation, communications, and utilities (8–9%), and mining (6–7%). The distribution of cross-border M&A across one-digit sectors is strikingly similar across the two samples.

If cross-country distances matter less for manufacturing because these distances are related to monitoring costs and such costs are less important for manufacturing sectors, then we would expect that manufacturing will have a bigger share of cross-border M&A than domestic M&A. Table 4 shows the number of acquisitions in manufacturing and non-manufacturing for both domestic and cross-border M&A activity across our sample years and for various sample countries. A universal pattern across all our differing samples of countries is that manufacturing accounts for a significantly larger share of cross-border M&A activity (column 6) than domestic M&A activity (column 3). For example, in our two samples of countries (top 50 and OECD), manufacturing accounts for only about 25–26% of targets acquired by domestic acquirers, but 34% of targets acquired by foreign firms (i.e., cross-border M&A). Across all top 10 target countries, the share of manufacturing targets is also always larger in the cross-border activity than in the domestic activity. These numbers suggest that cross-border M&A is relatively easier for manufacturing industries than non-manufacturing ones, and we next outline the empirical model we will use to more formally explore whether monitoring costs are a key mechanism in these differences we see in the raw data.

4. Model and empirical specification

The Head and Ries (2008) model views cross-border M&A as an international market for corporate control of productive assets, where the headquarters' monitoring cost of a (potential) subsidiary plays a key role in the cross-border M&A decision. Frictional costs associated with cross-border M&A stem from this monitoring cost because it is assumed that monitoring costs increase as the physical or cultural distance between the home and host countries increases. Our strategy is to test this monitoring-cost mechanism using cross-sectoral variation in monitoring costs. In order to do so we must first extend the Head and Ries (2008) model to accommodate sector-specific frictional costs.

The Head and Ries model is motivated by a simple inspection game, which is played between the headquarters (HQ) and its subsidiary. Without monitoring by the HQ, the manager of the subsidiary lacks incentives to exert effort to maximize the value of the subsidiary. Monitoring requires costs that are increasing in distance (both physical and cultural) between the HQ and its subsidiary. The subsidiary (manager) chooses whether to work or shirk. Gross profit depends on the contributions of the HQ and the subsidiary, which are denoted by a and b, respectively. The HQ always adds a, whereas the subsidiary adds b if it chooses to exert effort. The HQ simultaneously chooses whether to trust the subsidiary or monitor and verify for a cost of c that the subsidiary has worked. HQ pays w to the subsidiary, unless monitoring reveals that the subsidiary is shirking, in which case the subsidiary gets zero. Working generates gross output of $a + b$, but the subsidary incurs effort costs of e. Head and Ries (2008) make parameter assumptions that $b>w>e>c>0$, and then solve for a mixed strategy Nash equilibrium of the inspection game, which yields the following expression for the value of the subsidiary for the HQ:

$$v = a + b - 2\sqrt{bc} \tag{1}$$

As can be seen from Eq. (1), higher verification costs (c) lower the value of the subsidiary to the HQ. Head and Ries (2008) postulate the costs of monitoring (c) as an increasing function of $\mathbf{D}_{ij}$, which is a vector of physical and cultural distances between the parent country i and the host country j, and further specify the functional form of the costs related to these remoteness measures as $c_{ij} = (\frac{\mathbf{D}_{ij}\boldsymbol{\delta}}{2})^2$,where $\boldsymbol{\delta}$ is a vector of parameters that weight the distance measures. Substituting into Eq. (1), the value of an acquisition between country i and j is:

$$v_{ij} = a + b - \sqrt{b}\ \mathbf{D}_{ij}\boldsymbol{\delta} \tag{2}$$

Country-level physical and cultural distances may affect cross-border M&A in a number of other non-trivial ways than through monitoring costs, including transport of goods and the initial search for acquisition targets. Thus, the strong evidence for the role of these cross-border frictions in Head and Ries (2008) does not identify if monitoring costs are the mechanism for this relationship. Our test relies on sectoral variation across measures of monitoring intensity, so we begin our extension of their model with the simple assumption that monitoring costs also vary by sector (k), $c_{ijk} = (\frac{\mathbf{D}_{ijk}\boldsymbol{\delta}}{2})^2$, which then modifies Eq. (2) as follows:

$$v_{ijk} = a + b - \sqrt{b}\ \mathbf{D}_{ijk}\boldsymbol{\delta} \tag{3}$$

In order to derive an estimating equation from (3), we continue to follow Head and Ries (2008), while extending their model to account for sectoral variation. We assume that the HQ with the highest expected payoff (i.e., v) makes the highest bid and wins the auction for control of a subsidiary. Let π_{ijk} denote the probability that a HQ from country i takes control of a randomly drawn target in country j in industry k. Also, let K_{jk} denote the asset value of the entire stock of targets in the host country j in industry k. Then we can represent the expected bilateral FDI stocks as follows,

$$E\left[F_{ijk}\right] = \pi_{ijk}K_{jk}. \tag{4}$$

We follow Head and Ries (2008) in specifying π_{ijk}, by assuming that country i has m_i headquarters, each of which have different valuations for a given target in industry k in country j.[12] Note that this means that any firm in the acquiring country i (not just those in industry k) is an equally eligible bidder for a target in country j in industry k, allowing for all forms of cross-border M&A from conglomerate to horizontal to vertical. Heterogeneity in the valuations is introduced through the HQ value-added term a. We assume that the cumulative density of a takes the Gumbel (type-I extreme value): $\exp(-\exp(-x - \frac{\mu}{\sigma}))$, where μ is the location parameter and σ is the shape parameter. Using the results of Anderson, de Palma, and Thisse, (1992), p. 39, it can then be shown that π_{ijk} is given by the multinomial logit formula:

$$\pi_{ijk} = \frac{exp\left[\frac{\mu_i}{\sigma} + \ln(m_i) - \frac{\sqrt{b}}{\sigma}\mathbf{D}_{ijk}\boldsymbol{\delta}\right]}{\sum_\zeta exp\left[\frac{\mu_\zeta}{\sigma} + \ln\left(m_\zeta\right) - \frac{\sqrt{b}}{\sigma}\mathbf{D}_{\zeta jk}\boldsymbol{\delta}\right]} \tag{5}$$

Substituting (5) into (4), we can express expected bilateral FDI stocks as

$$\mathrm{E}\left[F_{ijk}\right] = \frac{m_i\ exp\left[\frac{\mu_i}{\sigma} - \frac{\sqrt{b}}{\sigma}\mathbf{D}_{ijk}\boldsymbol{\delta}\right]}{\sum_\zeta\ m_\zeta\ exp\left[\frac{\mu_\zeta}{\sigma} - \frac{\sqrt{b}}{\sigma}\mathbf{D}_{\zeta jk}\boldsymbol{\delta}\right]}K_{jk} \tag{6}$$

In order to obtain an estimating equation, we first define $\boldsymbol{\theta} \equiv (\frac{\sqrt{b}}{\sigma})\boldsymbol{\delta}$, which determines the FDI-impeding effect of the frictions that increase monitoring costs. Also, $E[F_{ijk}]$ depends only on the shares of HQs in each country, so we introduce

[12] In this formulation, we necessarily assume that the bidding process for each industry (k) is independent from the bidding process in other industries. This assumption is more plausible as the number of industries gets very large. Our empirical work is at the 3-digit SIC level, which means that we will have several hundred industries.

$s_i^m \equiv \frac{m_i}{\sum_\zeta m_\zeta}$ to represent a country's share of the world's bidders. And finally, we define $B_{jk} \equiv \sum_\zeta s_\zeta^m \exp[\frac{\mu_\zeta}{\sigma} - \mathbf{D}_{\zeta jk}\boldsymbol{\theta}]$ as the "bid competition" for targets in country j in industry k. Re-writing Eq. (6) in terms of these variables yields:

$$E\left[F_{ijk}\right] = \exp\left[\frac{\mu_i}{\sigma} - \mathbf{D}_{ijk}\boldsymbol{\theta}\right] s_i^m K_{jk} B_{jk}^{-1} \tag{7}$$

Eq. (7) now resembles the gravity equation where expected bilateral stocks are increasing in size variables connected to the origin and destination (s_i^m and K_{jk}) and decreasing in measures of bilateral distance. Higher bid competition in country j in industry k (i.e., B_{jk}) implies that a higher fraction of assets in country j in industry k will be taken by rivals from other countries, thereby reducing the expected bilateral stocks of HQs from country i.

Further re-arrangement of Eq. (7) gives us some insight into how the parameters of the model can be estimated:

$$E\left[F_{ijk}\right] = \exp\left[\frac{\mu_i}{\sigma} + \ln s_i^m + \ln K_{jk} - \ln B_{jk} - \mathbf{D}_{ijk}\boldsymbol{\theta}\right] \tag{8}$$

Eq. (8) shows that bilateral FDI can be separated into an origin i-specific term relating to its share of the world's HQs ($\ln s_i^m$) and their mean ability ($\frac{\mu_i}{\sigma}$), and a destination-industry jk-specific term relating to the share of target assets ($\ln K_{jk}$) and the competing set of bidders ($\ln B_{jk}$). We will denote $O_i \equiv \frac{\mu_i}{\sigma} + \ln s_i^m$ as the outward direct investment effect for origin i, and $I_{jk} \equiv \ln K_{jk} - \ln B_{jk}$ as the inward direct investment effect for industry k in destination j. Substituting these terms, we obtain the following expression for expected bilateral FDI stocks:

$$E\left[F_{ijk}\right] = \exp\left[\, O_i + I_{jk} - \mathbf{D}_{ijk}\boldsymbol{\theta}\right]. \tag{9}$$

In order to move from the expected values determined in the theory to the actual values of FDI recorded in the data set, we define $\eta_{ijk} \equiv \frac{F_{ijk}}{E[F_{ijk}]}$ as the ratio of actual to expected bilateral FDI stocks. Using Eq. (9),

$$F_{ijk} = E\left[F_{ijk}\right]\eta_{ijk} = \exp\left[\, O_i + I_{jk} - \mathbf{D}_{ijk}\boldsymbol{\theta}\right]\eta_{ijk}. \tag{10}$$

As Head and Ries (2008) shows, with the right assumption on the error term, we can use maximum likelihood estimation of a count data model (such as a (quasi-)Poisson) to estimate the vector of parameters of interest in the model, $\boldsymbol{\theta}$. We can control for the outward (O_i) and inward (I_{jk}) effects using sets of parent-country and host-country-by-industry fixed effects, respectively. However, as has become standard in gravity-type estimations, we instead include a more complete set of fixed effects that fully absorbs these fixed effects, as well as controlling for unobserved variation in other dimensions. This inclusive set of fixed effects is comprised of country-pair (ij), parent-country-by-industry (ik), and host-country-by-industry (jk) fixed effects.

The focus of our analysis is the impact of the vector of frictions, $\mathbf{D}_{ijk}$, on cross-border M&A. In Head and Ries (2008), these frictions only vary by cross-border pair. As discussed above, this makes it challenging to identify the effects as due to monitoring costs because there are a number of other reasons why cross-border distances could limit cross-border M&A. In order to identify whether monitoring costs represent a mechanism for the inverse relationship between bilateral-country distances and FDI, we pursue a strategy similar to Rajan and Zingales (1998), which has been used in many subsequent empirical studies.[13] From the O*NET data described above we have sectoral information on the degree to which monitoring and related activities matter across sectors. If greater cultural and physical distances increase monitoring costs, then we expect that the FDI-reducing impact of these distances will be greater for sectors where monitoring is more important. Formally, we model this as $\mathbf{D}_{ijk} = M_k \times \mathbf{D}_{ij}$, where M_k is the O*NET variable measuring the "monitoring importance" across sectors. Note that the country-pair (ij) fixed effects control for any other potential mechanisms by which bilateral distances ($\mathbf{D}_{ij}$) may directly affect FDI, as well as any other country-pair control variables that empirical FDI studies often include and find to have statistical support.

Our vector of physical and cultural distance measures include the same ones used by Head and Ries (2008). These are $Distance_{ij}$, a measure of the physical distance between the home and the host country, $LangDist_{ij}$, a measure of the dissimilarity of language between the two countries, and an indicator when the two countries do not have a past colonial relationship, $NoColony_{ij}$.[14] These data come from the CEPII website (www.cepii.fr) and have been used by many others for statistical studies of international economic activity.

We also include two cultural distance variables not included in Head and Ries (2008), but often used in other studies. The first is $CultureDist_{ij}$, measuring the cultural distance between the parent and the host country. We use Kogut and Singh's (1988) approach which is a composite index based on the weighted difference between the four cultural dimensions (i.e. power distance, uncertainty avoidance, masculinity/femininity, and individualism) of each country. The second cultural variable we include is religious distance, $ReligDist_{ij}$. We use information from the CIA Factbook to gather shares of population in each country that identify with the following religions: Catholic, Protestant Christian, Muslim, Buddhist, Hindu, Orthodox

[13] In the international trade and FDI literature, such studies include Alfaro et al. (2004), Manova (2008), Chor and Manova (2012), and Blonigen (2015).

[14] One difference from Head and Ries (2008) is that we define all these variables in terms of frictions, so that they all have an expected inverse correlation. We also follow Melitz and Toubal (2014) and use the percentage of people from each country that share a common native language (rather than official language) and invert the measure so it represents a language dissimilarity measure.

or Jewish. For each country pair we total the share (in decimal form) of their populations with a common religion and then subtract from one.

Our final empirical specification is:

$$F_{ijk} = E\left[F_{ijk}\right]\eta_{ijk} = \exp\left[\gamma_{ij} + \mu_{ik} + \ \rho_{jk} - \left(M_k \times \mathbf{D}_{ij}\right)\theta\right]\eta_{ijk}, \tag{11}$$

where $\{\boldsymbol{\theta}\}$ are the set of parameters to be estimated using Pseudo-Poisson Maximum Likelihood (PPML) methods when using multiple sets of high-dimesional fixed effects.[15] The variables γ_{ij}, μ_{ik}, and ρ_{jk} represent the sets of country-pair (*ij*), parent-country-by-industry (*ik*), and host-country-by-industry (*jk*) fixed effects, respectively.

Before turning to our results, we address the appropriateness of the Rajan-Zingales method of variable construction and identification for our context. Unlike the Rajan and Zingales (1998) study examining how much financial dependence of firms affects economic growth, we think the possiblity of reverse causality or other sources of endogeneity are much less likely in our context. Cross-border M&A activity is unlikely to have much impact on the inherent costs of monitoring distant affiliates or variation in these monitoring costs across industries. The only argument we can think of would be the possibility that greater cross-border M&A within an industry and bilateral country pairing could reduce monitoring costs due to economies of scale, especially if it is the same firm purchasing multiple targets. This would actually attenuate our coefficient estimates and lead to an underestimate of the effects of monitoring costs on cross-border M&A activities. But this seems unlikely to be a very large source of bias.

However, we have a similar issue to Rajan and Zingales (1998) in considering whether this interaction variable is a good proxy for the underlying variable. In our setting, we do not observe monitoring costs directly for a specific industry and bilateral-country pair (i.e., we don't have a measure of M_{ijk}). Instead, we have M_k and $\mathbf{D}_{ij}$. In order for $M_k \times \mathbf{D}_{ij}$ to be a good proxy for M_{ijk}, we need to make an assumption that our measure of $\mathrm{M_k}$ is valid for all i-j country pairs. Our data for M_k is based on U.S. data, and is based on the level and importance of monitoring, communication and interpersonal skills needed for a particular occupation, as well as the relative shares of occupations in an industry.[16] These assumptions are more likely to be invalidated when technologies available to labor are substantially different. For example, a factory worker's tasks and needed skills could be significantly different in a factory with substantial automation than one without. Also, the share of labor across occupations in a firm could be quite different depending on its access to automation, information technologies, etc. Our focus on the top 50 M&A countries, which are also generally the most advanced countries, makes these assumptions more likely to hold. Technologies in these countries are similar enough that one can expect that the skills needed for a given occupation and relative shares of various occupations are very similar.

5. Empirical results

We begin the empirical results by estimating Eq. (11) using PPML methods to estimate the impacts of cross-border frictions on M&A activity for our full sample of cross-border M&A transactions between the top 50 countries over the 2005–2014 period. We then explore the robustness of our results to alternative samples and specifications, as well as different measures of monitoring importance. Finally, we turn to examining the extent to which the monitoring cost effect of FDI explains the substantial differences we see in cross-border M&A activity across industrial sectors.

5.1. Evidence for the monitoring-cost effect on FDI

Table 5 provides the PPML estimates for our base specification for the full sample of Top 50 countries, where each of the first five columns separately introduces the interaction of the monitoring importance variable (M) with a cross-border friction. We then include all the interaction terms in the specification in the last column. All specifications include country-pair fixed effects, parent-country-by-industry fixed effects, and host-country-by-industry fixed effects. Standard errors are clustered at the 3-digit SIC industry level.

The results provide strong statistical evidence for the monitoring-cost effect on cross-border M&A activity. Separately, each of the interaction terms has the expected negative coefficient and is statistically significant at the 1% level with the exception of the colonial relationship interaction, which is at the 5% level. Due to multicollinearity, three of the five individual coefficients on the interaction terms are insignificant in the last column, but the interaction terms are jointly significant at the 1% level (F-test value of 25.20 with a p-value less than 0.001).

The economic effects are significant as well. Using our column 6 estimates, we find that a standard deviation increase in monitoring importance decreases predicted cross-border M&A activity by 36.3% at the means of our data. This marginal effect is statistically significant at the 1% level. There is some asymmetry in this effect, as a one standard deviation ***decrease*** in the importance of monitoring increases predicted M&A activity by 57.4% (also statistically significant at the 1% level). These marginal effects are calculated assuming that the independent effect of monitoring importance on predicted M&A activity is held constant because it is absorbed in the parent-country-by-industry and host-country-by-industry fixed effects,

[15] We rely on the "ppmlhde" command developed by Correia, Guimarães, and Zylkin (2019) for our estimations.

[16] To use a concrete example, the types of skills required to be, say, a cashier, need to be generally the same across all the countries in our sample as in the U.S. Likewise, the relative shares of occupations in say, a retail clothes store (cashier, inventory control, management, marketing, etc.), need to be generally the same across all the countries in our sample as in the U.S.

Table 5
Pseudo-Poisson Maximum Likelihood Estimates of the Determinants of Cross-Border M&A –Full Sample.

Independent Variables	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
M x Dist	−0.938***					−0.606**
	(0.294)					(0.302)
M x LangDist		−3.617***				−1.165
		(0.881)				(1.056)
M x CultDist			−0.883***			−0.481**
			(0.221)			(0.216)
M x NoColony				−1.047**		−0.379
				(0.452)		(0.636)
M x ReligDist					−6.583***	−2.542
					(1.557)	(1.600)
Parent Country x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Host Country x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181,709	181,709	170,662	181,709	181,709	170,662
R-squared	0.630	0.630	0.635	0.630	0.630	0.635
F-test for Monitoring Interactions					25.20	
(p-value of F-test)						(0.000)

Notes: Coefficient estimates are from a Pseudo-Poisson Maximum Likelihood specification where the dependent variable is the number of merger and acquisitions in a 3-digit SIC industry between a bilateral pair from the Top 50 countries (as defined in Appendix A) over the period 2005 - 2014. Descriptions and sources for our independent variables are reported in Appendix B. The reported F-test and associated p-value is a joint significance test for all five monitoring interaction terms. Standard errors, clustered at the 3-digit SIC level, are in parentheses below each coefficient estimate. We denote coefficients that have a p-value less than 0.01, 0.05, and 0.10 with ***, **, and *, respectively.

Table 6
Pseudo-Poisson Maximum Likelihood Estimates of the Determinants of Cross-Border M&A – OECD only.

Independent Variables	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
M x Dist	−0.719**					−0.484
	(0.351)					(0.357)
M x LangDist		−3.679***				−1.750*
		(0.921)				(0.984)
M x CultDist			−1.132***			−0.655***
			(0.222)			(0.233)
M x NoColony				−1.009**		−0.099
				(0.468)		(0.568)
M x ReligDist					−7.765***	−3.627*
					(1.875)	(2.131)
Parent Country x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Host Country x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,272	80,272	80,272	80,272	80,272	80,272
R-squared	0.665	0.665	0.665	0.665	0.665	0.665
F-test for Monitoring Interactions						29.91
(*p*-value of F-test)						0.000

Notes: Coefficient estimates are from a Pseudo-Poisson Maximum Likelihood specification where the dependent variable is the number of merger and acquisitions in a 3-digit SIC industry between a bilateral pair from the Top 50 countries (as defined in Appendix A) over the period 2005 - 2014. Descriptions and sources for our independent variables are reported in Appendix B. The reported F-test and associated p-value is a joint significance test for all five monitoring interaction terms. Standard errors, clustered at the 3-digit SIC level, are in parentheses below each coefficient estimate. We denote coefficients that have a p-value less than 0.01, 0.05, and 0.10 with ***, **, and *, respectively.

just as the independent effect of the physical and cultural distances are held constant because they are absorbed by the country-pair fixed effects.

5.2. Alternative samples and measurements of monitoring importance

We explore the robustness of our results in a variety of ways. Perhaps the most obvious check is to reduce our sample to only the cross-border M&A transactions between OECD countries. As indicated earlier, the majority of cross-border transactions in the world occur between the OECD countries and, relatedly, these are the richer and more-developed countries. Because of this there may be structural differences in how cultural and physical distance frictions operate on international transactions between these countries than on transactions involving a non-OECD country.

Table 6 provides analogous statistical results for the sample of cross-border M&A activity between OECD countries as those reported in Table 5 for the full sample. The results are qualitatively very similar. The interactions of monitoring

Table 7
Marginal Effect of Monitoring Costs on Cross-border M&A Activity and Robustness of the Effect.

	Full Sample	***OECD***	***Non-OECD***	***1995–2004***	***Include Domestic***	***Separate O*NET categories***	***Principal Component***	***O*NET Monitoring Skill***
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***
F-Test for Joint Significance of Monitoring Interactions	25.20	29.91	13.84	17.19	31.31	24.40	24.94	23.51
(p-value)	(0.000)	(0.000)	(0.017)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Reduction in Cross-Border M&A Activity for a Standard Deviation Increase in Monitoring Importance	−36.34%	−36.98%	−56.30%	−34.73%	−19.83%	−31.74%	−35.84%	−32.32%
F-test	18.72	13.71	21.85	14.03	6.531	12.08	16.25	13.78
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.001)	(0.001)	(0.000)

Notes: Calculations from estimations using a Pseudo-Poisson Maximum Likelihood specification where the dependent variable is the number of merger and acquisitions in a 3-digit SIC industry between bilateral pairs of countries. Except for columns titled "OECD" and "non-OECD", the sample of countries includes all top 50 countries in the full sample. Also, except for the column "1995 - 2004″, the time period covers cumulative cross-border M&As over 2005 - 2014. All regressions include parent-country-by-industry fixed effects, host-country-by-industry fixed effects as well as country-pair fixed effects. The first reported F-test and the associated p-value correspond to a joint significance test for all five monitoring interaction terms of interest. The last reported F-test and associated p-value correspond to the null hypothesis that the predicted value of cross-border M&As from a one standard deviation increase in monitoring importance is not statistically different from the predicted value of cross-border M&As evaluated at sample means.

importance with the physical and cultural distance frictions are all negative and statistically significant when introduced separately. When the full set of interactions of monitoring importance with cultural and physical distance frictions are introduced in the final column of Table 6, they all have the expected negative sign, but only three of the coefficients on the interactions are statistically significant. However, just as with the full sample, these interactions are jointly statistically significant at the 1% level and economically signficant as well. A one-standard deviation increase in monitoring importance is associated with a decline in the dependent variable of 40% through these interactions, which is very close in magnitude to the effect observed in the full sample (36.3%). Similarly, a one standard deviation decrease in the importance of monitoring increases predicted M&A activity by 58.1% for the OECD sample, nearly identical to the 57.4% effect in the full sample. In summary, the results for the OECD-only sample are surprisingly similar to the full sample.

Table 7 provides evidence that the joint significance of the monitoring cost interactions and their joint marginal impact on cross-border M&A activity is robust to a variety of other robustness checks. Columns 1 and 2 show results from the full sample and the OECD-only sample that we just presented. Column 3 shows the results when we estimate our model on the sample of observations that involve a non-OECD country.[17] While our estimates are slightly less precise for the non-OECD example, the marginal effects are larger in this sample than the OECD sample with a standard deviation increase in monitoring importance associated with over a 50% decline in cross-border M&A activity.

Column 4 shows that our key results are robust over time by estimating our model using data from the prior decade (1995–2004) for our full sample of countries. The interaction terms continue to be jointly significant at the 1% level and the marginal effect is nearly identical to that in our main sample (2005–2014).

Column 5 shows the robustness of our results when we include domestic acquisitions in the sample. Domestic acquisitions number roughly four times as many as the cross-border M&A transactions in the data (see Table 4). However, an important issue is that measuring distances within a country are often not analogous to measuring them between countries, introducing measurement issues. In order to include domestic acquisitions in our sample we use data on internal distance constructed by CEPII to measure physical distance.[18] We also make the assumption that language distance, cultural distance and colonial relations are zero for domestic acquisitions. For religious distance we apply the same computation methodology as for bilateral country pairs. Despite introducing these non-trivial measurement issues into our specification when including domestic acquisitions, our interactions between monitoring importance and distances continue to be jointly significant, though the estimated marginal effect for a one-standard deviation increase of monitoring importance goes down in absolute terms from a decline in predicted M&A activity of around 36% in our base results to about 20%.

Columns 6 through 8 examine the robustness of our results to variations in how we measure monitoring importance. Recall from Section 2 that our monitoring importance variable is an average measure across "cultural skills", "language skills", and "monitoring skills" identified in the O*NET database. As an alternative, we created a new measure of monitoring importance derived only from monitoring skills. We then analogously created a cultural importance measure from the cultural skills data, and a language importance measure from the langugage skills data. We interacted this new monitoring importance measure with physical distance (*Dist*), the language importance measure with language distance (*LangDist*), and the

[17] This could either be when one of the countries (acquirer or target) is non-OECD while the other involved country is OECD, or when both the acquirer and target countries are non-OECD.

[18] This measure is based on the radius of a circle with the area equal to the size of a country. This is not a perfect measure of internal distance because the distribution of firms within a country is often lumpy and concentrated in certain (urban) areas.

cultural importance measure with our remaining cultural distance variables (*CultDist, NoColony*, and *ReligDist*). Column 6 shows that we get qualitatively identical results when we interact these alternative skill importance variables with our cultural, language and physical distance measures. In column 7, we form a principal component from these three terms (O*NET monitoring importance, O*NET cultural importance, and O*NET language importance) and interact the principal component with our cultural, language and physical distance terms. This too yields qualitatively identical results. Lastly, in column 8, we strip down the monitoring importance variable to just one of the thirteen O*NET occupational skills - the "monitoring" skill. Once again we find qualitatively identical results to our base results.

In summary, the evidence for a statistically and economically significant effect of monitoring importance on cross-border M&A activity is highly robust across a number of alternative samples and measures of monitoring importance. A standard deviation increase in monitoring importance is associated with a decreased level of cross-border M&A activity that ranges from around 20% to over 56%.

5.3. Identification: could our monitoring importance variable be proxying for other effects?

In this section, we address whether our results may be spurious correlations because our measure of monitoring importance could be proxying for something else. The main concern for our paper based on past literature is that our measure of monitoring importance is really a proxy for the knowledge-intensity of a sector and that we are simply verifying/replicating the prior results of Keller and Yeaple (2013) and Bahar (2018). These papers hypothesize that distances are a greater friction for FDI in knowledge-intensive sectors because communicating the knowledge needed for production by the affiliate is more difficult, requiring a greater amount of imported inputs for the foreign affiliate from the parent. This means that distance is more costly for knowledge-intensive sectors because of the greater need to rely on shipping physical goods with embedded knowledge to affiliates.

To confirm their hypothesis, Keller and Yeaple (2013) show that FDI activity in manufacturing sectors is decreasing in the interaction of a number of O*NET measures meant to proxy for knowledge-intensiveness at the industry level with distance, similar to our identification strategy. The O*NET measures they use are the importance of 1) Analyzing data, 2) Processing information, 3) Updating and using relevant information, and 4) Judgement and decision making. Is our measure of monitoring importance identifying something different from these measures of knowledge-intensity of a sector?

Table 8 shows it is. The first column provides our results from the full sample (Column 6 of Table 5) for comparison purposes. The next four columns then provide results when we separately interact each of the four knowledge-intensity O*NET measures from Keller and Yeaple (2013) with our distance measures and include them in a regression with our monitoring importance interactions with distances.[19] In all four cases, our results are qualitatively identical to our base results when we include the interactions of our distance variables with the Keller-Yeaple measures of knowledge-intensity – our monitoring interactions are jointly significant and the effect of a standard deviation increase in monitoring importance decreases M&A activity between 35 and 50%.[20]

Bahar (2018) proposes a much different measure of knowledge-intensity at the industry level. He instead uses O*NET data to construct a measure of the relative amount of related experience and training workers need for the various occupations in an industry.[21] In column 6 of Table 8, we show results when we include interactions of Bahar's measure of knowledge-intensity with our distance measures in our base specification. As with the interactions involving the Keller-Yeaple measures of knowledge-intensity, our results are robust and continue to show a strong statistical and economic significance of our interactions of the distance variables with our measure of monitoring importance.

A final related question that we examine is whether the importance of monitoring is isomorphic with the labor-intensity of an industry. It may be that monitoring simply increases as the labor-capital ratio goes up regardless of the type of labor that is used or the activities that are undertaken. To explore this, we first construct a labor-to-capital ratio using U.S. Bureau of Economic Analysis data on the numbers of full-time equivalent employees by industry as a measure of labor and the value of fixed-cost net capital stock of private nonresidential fixed assets (which include equipment, structures, and intellectual property products) as a measure of capital.[22] We interact this labor-to-capital measure with our distance variables and include these interaction terms into our baseline specification. Column 7 of Table 8 reports the results. The coefficient estimates on our monitoring-importance interactions are hardly affected by including these interaction terms, indicating that monitoring activities are not isomorphic with labor-intensity.[23]

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[19] See the online appendix in Keller and Yeaple (2013) for details on the construction of the four O*NET variables of knowledge intensity by manufacturing industries. We follow their procedure to replicate these measures.

[20] The coefficients on the interactions of our distance measures with the knowledge-intensity variables from Keller and Yeaple (2013) in Table 8 are generally insignificant and surprisingly positive and significant for the interaction with physical distance. However, our specification is much different than in Keller and Yeaple (2013), particularly because their dependent variable is not a measure of total FDI, but a measure of "local [foreign affiliate] sales to non-affiliated parties." Our results are robust regardless of which of the four measures of knowledge-intensity we use and regardless of the subset of distance interactions with these knowledge-intensity variables that we include in the estimation.

[21] See Bahar (2018) for more details about construction of this variable. We thank Dany Behar for sharing his data with us.

[22] See Appendix B for more details on the construction of the labor-to-capital ratio by industry.

[23] In unreported results, we also show that defining our monitoring variable as only the importance of "management of personnel" does not yield qualitatively different results than when we define it as only the importance of "management of material resources", further suggesting that labor intensity is not the main driver of our findings.

Table 8
Pseudo-Poisson Maximum Likelihood Estimates with Alternative Measures of Monitoring Costs –Full Sample.

Alternative O*NET measure:	This page (1)	O*NET Analyze Data (2)	O*NET Process Information (3)	O*NET Update Information (4)	O*NET Judge Information (5)	Bahar (6)	L/K Ratio (7)
M x Dist	−0.606**	−1.422***	−1.412***	−1.153***	−0.847**	−0.909***	−0.566**
	(0.302)	(0.380)	(0.374)	(0.353)	(0.361)	(0.303)	(0.289)
M x LangDist	−1.165	−1.102	−0.957	−0.689	−1.038	−1.181	−0.962
	(1.056)	(1.076)	(1.087)	(1.082)	(1.130)	(1.025)	(1.093)
M x CultDist	−0.481**	−0.435**	−0.346*	−0.365*	−0.234	−0.524**	−0.481**
	(0.216)	(0.204)	(0.200)	(0.200)	(0.200)	(0.212)	(0.214)
M x NoColony	−0.379	−0.354	−0.510	−0.464	−0.586	−0.330	−0.344
	(0.636)	(0.636)	(0.650)	(0.647)	(0.692)	(0.615)	(0.643)
M x ReligDist	−2.542	−0.938	−1.055	−0.982	−1.276	−2.618	−2.405
	(1.600)	(1.604)	(1.647)	(1.589)	(1.611)	(1.644)	(1.601)
*Alternative O*NETx Dist*		0.138***	0.138***	0.098***	0.360	0.006***	−0.025
		(0.036)	(0.031)	(0.026)	(0.235)	(0.002)	(0.017)
*Alternative O*NET x LangDist*		−0.007	−0.028	−0.087	−0.117	0.000	−0.106**
		(0.081)	(0.088)	(0.060)	(0.721)	(0.003)	(0.042)
*Alternative O*NET x CultDist*		−0.007	−0.021	−0.018	−0.365*	0.001	0.000
		(0.012)	(0.016)	(0.014)	(0.188)	(0.001)	(0.006)
*Alternative O*NET x NoColony*		−0.011	0.017	0.006	0.300	−0.002	−0.017
		(0.037)	(0.044)	(0.038)	(0.428)	(0.002)	(0.022)
*Alternative O*NET x ReligDist*		−0.295***	−0.290**	−0.320***	−2.514**	0.002	−0.100
		(0.109)	(0.134)	(0.100)	(1.201)	(0.006)	(0.075)
Parent Country x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host Country x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,662	170,662	170,662	170,662	170,662	170,662	170,662
R-squared	0.635	0.635	0.635	0.635	0.635	0.635	0.635
F-test for Monitoring Interactions	25.20	23.92	23.33	19.70	14.76	34.07	27.04
(*p*-value of F-test)	(0.000)	(0.000)	(0.000)	(0.001)	(0.011)	(0.000)	(0.000)
Reduction in Cross-Border M&A Activity for a Standard Deviation Increase in Monitoring Importance	−50.35%	−50.12%	−43.91%	−38.13%	−43.96%	−34.53%	
F-test		22.68	23.38	21.51	12.84	30.04	17.84
(*p*-value)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Coefficient estimates are from a Pseudo-Poisson Maximum Likelihood specification where the dependent variable is the number of merger and acquisitions in a 3-digit SIC industry between a bilateral pair from the Top 50 countries (as defined in Appendix A) over the period 2005 - 2014. A description and sources for our independent variables are reported in Appendix B. Columns 2 to 7 include control variables motivated by existing papers in the literature (i.e., alternative O*NET measures interacted with friction terms). The first reported F-test for monitoring interactions and its associated p-value correspond to a joint significance test for all five monitoring interaction terms of interest. The last reported F-test and associated p-value correspond to the null hypothesis that the predicted value of cross-border M&As from a one standard deviation increase in monitoring importance is not statistically different from the predicted value of cross-border M&A evaluated at sample means. Standard errors, clustered at the 3-digit SIC level, are in parentheses below each coefficient estimate. We denote coefficients that have a p-value less than 0.01, 0.05, and 0.10 with ***, **, and *, respectively.

In conclusion, the statistical economic significance of the estimated monitoring effects is hardly affected by the proposed robustness exercises. Across all columns reported in Table 8, a one-standard deviation increase in monitoring importance is associated with a decline of 35% to 50% in cross-border M&A activity. These results reported at the bottom of Table 8 are surpisingly similar in magnitude to the corresponding marginal effects reported in Table 7.

5.4. Monitoring importance explains a significant portion of the difference in cross-border M&A activity across industrial sectors

Given the robustness of our results, we are now in a position to conduct an important exercise with our estimates. As discussed in the introduction, manufacturing has a disproportionate share of FDI activity in the world economy relative to other sectors and it also has occupations that generally require less monitoring skills. An important question is the extent to which this monitoring importance can explain differences in cross-border M&A activity in manufacturing versus other sectors. We use our estimates from the final column of Tables 5 and 6 to directly examine this question.

Table 9 provides our analysis for both the full sample (Panel A) and the OECD-only sample (Panel B). The first column of data provides the predicted number of bilateral cross-border M&As for the average 3-digit SIC industry within a given broadly defined sector at the means of all the regressors. For example, the model's predicted number of cross-border M&A transactions between any pair of countries in the full sample for a 3-digit SIC industry in manufacturing is 0.277 at the

Table 9
The Effect of Monitoring Costs on Predicted Cross-Border M&A by Sector.

PANEL A: Full Sample					
	Predicted Value of Dependent Variable		**F-test statistical significance**		
		With the Same			
	At Means of Data	**Monitoring Costs as Manufacturing**	**Percent Difference**	**(p-value)**	**Obs**
Manufacturing	0.277	0.277	0.00%	n.a.	73,957
Non-Manufacturing	0.400	0.609	52.25%	10.70 (0.001)	96,705
Mining	0.632	0.569	−9.97%	7.12 (0.008)	6800
Construction	0.178	0.184	3.37%	8.07 (0.004)	5087
Transportation, communications, and utilities	0.285	0.324	13.68%	8.50 (0.004)	18,996
Wholesale trade	0.195	0.393	101.54%	13.65 (0.00)	14,070
Retail trade	0.160	0.430	168.75%	17.26 (0.00)	10,873
Finance, insurance, and real estate	0.441	1.012	129.48%	15.00 (0.00)	16,412
Services	0.719	0.862	19.89%	8.78 (0.003)	24,467
PANEL B: OECD Sample					
	Predicted Value of Dependent Variable		**F-test statistical significance**		
		With the Same			
	At Means of Data	**Monitoring Costs as Manufacturing**	**Percent Difference**	**(p-value)**	**Obs**
Manufacturing	0.398	0.398	0.00%	n.a.	34,838
Non-Manufacturing	0.578	0.887	53.46%	7.83 (0.005)	45,434
Mining	1.053	0.958	−9.02%	5.30 (0.021)	2368
Construction	0.246	0.252	2.44%	5.84 (0.016)	2697
Transportation, communications, and utilities	0.422	0.478	13.27%	6.16 (0.013)	8582
Wholesale trade	0.294	0.59	100.68%	9.86 (0.002)	6765
Retail trade	0.222	0.626	181.98%	12.87 (0.000)	5260
Finance, insurance, and real estate	0.592	1.351	128.21%	10.86 (0.001)	7559
Services	1.086	1.293	19.06%	6.26 (0.012)	12,203

Notes: The first column of data provides the predicted number of bilateral cross-border M&As for the 10-year period (2005–2014) for 3-digit SIC codes connected with the listed sector at the means of all the regressors. Predictions are based on the estimates from column 6 of Table 5 for Panel A (full sample), respectively column 6 of Table 6 for Panel B (OECD-only sample). Column 2 provides the predicted value of the dependent variable when we modify the data so that the sector has the same level of monitoring importance (M) as manufacturing, keeping the level of all other variables at their means. Column 3 provides the percentage difference between columns 1 and 2 to show how much the predicted number of cross-border M&As changes when we put the sector's monitoring importance the same as manufacturing, and column 4 provides the F-test and associated p-value indicating the statistical significance of this difference. Column 5 reports the number of observation used for each estimation exercise.

means of the data. The analogous number for a non-manufacturing 3-digit SIC industry is 0.400. These averages increase by about 40% for the OECD-only sample with a 0.398 predicted value for manufacturing and 0.578 for non-manufacturing.

In column 2, we provide the predicted value of the dependent variable when the non-manufacturing sector has the same level of monitoring importance as manufacturing, keeping the level of all the other variables in the regressor set at their means. Column 3 provides the percentage difference between columns 1 and 2 to show how much the predicted number of cross-border M&As changes when we put the sector's monitoring importance at the same level as seen in manufacturing, and column 4 provides the F-test and associated p-value indicating the statistical significance of this difference.

As Table 9 shows, M&A activity would be higher for all non-manufacturing sectors (with the exception of mining) if monitoring importance would be at the same level as the manufacturing sector. On average, our estimates suggest that cross-border M&A activity would be 52.25% higher in the non-manufacturing sectors in our full sample, and 53.46% higher in the OECD-only sample. Non-manufacturing sectors are highly heterogeneous, spanning mining to services, so rows 3 through 9 provide the analysis for these sectors at the 1-digit SIC level. The results follow directly from the summary statistics in Table 1 in terms of which sectors require a greater amount of monitoring given their occupational composition. If monitoring importance were as low as that required in manufacturing, the high-monitoring sectors of wholesale trade, retail trade, and finance, insurance, and real estate would all see their cross-border M&A activity more than double according to our estimates. There would be much smaller increases (between 2 and 20%) in services, construction and transportation, communications, and utilities, and an actual decrease of around 9–10% in the mining sector where monitoring is less important than in manufacturing. Overall, monitoring importance is a highly significant factor in explaining lower cross-border M&A activity in non-manufacturing, especially for the wholesale trade, retail trade, and finance, insurance, and real estate sectors.

6. Conclusion

Prior literature nearly always finds that physical and cultural distances significantly impede a wide range of international economic phenomena. However, while there are a myriad of possible explanations for why these frictions are so significant, there is typically little evidence for which mechanisms are truly responsible for their effects.

In this paper, we provide a way to identify the role of monitoring costs as a mechanism behind the deleterious effects of physical and cultural distance on cross-border M&A activity, as proposed by Head and Ries (2008). We find significant evidence for this channel and show that differences in monitoring importance can explain a significant portion of the variation in cross-border M&A we observe across sectors of the economy. In robustness tests, we show that this effect is separately identifiable in our data from the evidence that distance has a greater negative impact on knowledge-intensive industries, as shown by previous literature.

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Appendix A

OECD Countries		Additional Top 50 Target Countries	
Australia	Luxembourg	Argentina	Malaysia
Austria	Mexico	Brazil	Peru
Belgium	Netherlands	Bulgaria	Philippines
Canada	New Zealand	Chile	Romania
Czech Republic	Norway	China	Russia
Denmark	Poland	Colombia	Singapore
Finland	Portugal	Hong Kong	South Africa
France	South Korea	Iceland	Taiwan
Germany	Spain	India	Thailand
Greece	Sweden	Indonesia	Ukraine
Hungary	Switzerland	Israel	Vietnam
Ireland	Turkey		
Italy	United Kingdom		
Japan	United States		

Appendix B

Variable Description and Sources

Dependent Variable

Merger and Acquistion (M&A) Activity

Count of M&A transactions from one country (acquirer country) into another country (target country) in a 2-digit SIC sector during a five-year period starting with the 1985–1989 period through the 2010–2014 period. Thomson Reuters SDC Platinum M&A Database is the source for these data.

Independent Variables

Monitoring Importance (M)

The Occupational Information Network (O*NET) developed by the U.S. Department of Labor provides information on the skills and abilities required in over 950 occupations within the U.S. economy. This can be accessed at the website: https://www.onetonline.org.

For each occupation, experts assess and rank the relevance of 35 distinct skill categories (e.g., coordination, negotiation, active listening, etc.). We focus on skills for which the relevance of each skill is evaluated in two ways: 1) the “importance” of a skill in a given occupation is measured by a score from 1 (less important) to 5 (very important); and 2) the “level” of a skill required in a given occupation is measured by a score from 0 (minimum level) to 7 (highest proficiency level). The two scores need not be correlated, for example, when a particular skill such as speaking comprehension is very important in a particular occupation, however at a level that is not very advanced or very sophisticated.

We identify 13 skills that are potentially related to monitoring an affiilate in a foreign country and list them here with their O*NET description[24]:

Monitoring skills:

a) **Coordination** - Adjusting actions in relation to others’ actions.
b) **Management of material resources** - Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.
c) **Management of personnel** - Motivating, developing, and directing people as they work, identifying the best people for the job.
d) **Monitoring** - Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action

[24] The full list of O*NET skills are at https://www.onetonline.org/find/descriptor/browse/Skills/.

Cultural skills:

a) **Negotiation** - Bringing others together and trying to reconcile differences.
b) **Persuasion** - Persuading others to change their minds or behavior.
c) **Service orientation** - Actively looking for ways to help people.
d) **Social perceptiveness** - Being aware of others' reactions and understanding why they react as they do.

Language skills:

a) **Active listening** - Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
b) **Instructing** - Teaching others how to do something.
c) **Reading comprehension** - Understanding written sentences and paragraphs in work related documents.
d) **Speaking** - Talking to others to convey information effectively.
e) **Writing** - Communicating effectively in writing as appropriate for the needs of the audience.

To construct an O*NET skill score for each of the 13 skills at the 2-digit SIC industry level, we implement the following steps:

1. For each skill level by occupation, we multiply the importance score by the level score to obtain a unique ranking value of that skill for that occupation. We then rescale the resulting score to take values between 0 and 1.
2. Occupations in O*NET database are recorded using SOC 8-digit classification for 2010. We average the unique O*NET occupation scores at the SOC 6-digit level and then use a crosswalk to convert the 2010 SOC codes to the corresponding 2000 SOC codes (using a crosswalk provided by the BLS:
3. https://www.bls.gov/soc/soc_2000_to_2010_crosswalk.xls).
4. We collected data from the Occupational Employment Statistics (OES) Survey provided by the BLS on employment by 2-digit SIC sectors across SOC occupation codes for year 2000 (https://www.bls.gov/oes/tables.htm) and then construct for each 2-digit SIC industry the employment share of all occupations related to Management (SOC 11), Business and Financial Operations (SOC 13), as well as Sales and Related occupations (SOC 41).
5. Using 2000 SOC codes as identifiers, we merge the O*NET occupation scores with the employment shares of managerial/business/sales occupations within each 2-digit SIC industries.
6. Using the 2000 employment shares as weights, we aggregate the O*NET skill scores across the selected managerial/business/sales occupations to obtain average O*NET skill scores at SIC 2-digit level.

As described in the text, our primary measure of monitoring importance takes the simple average of these 13 O*NET skill scores.

Geographic distance (*Dist*)

This is a population-weighted bilateral distance measure that comes from the GeoDist database at CEPII (http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6).

A benefit of using CEPII data is that it provides information on internal distances for our observations where the acquirer and target countries are the same (i.e., domestic M&A)

Language distance (*LangDist*)

We begin with a measure of common native languages between countries that is a continuous variable between 0 and 1 measuring the percentage of people from each country that share a common native language. This was developed by Melitz and Toubal, 2014, and is available as part of the Language database at CEPII: http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=19. We construct our language distance variable as 1 minus the common native language value.

Cultural distance (*CultDist*)

As described in the text, we use Kogut and Singh's (1988) approach to constructing this variable which is a composite index formed based on the weighted difference between the four cultural dimensions (i.e. power distance, uncertainty avoidance, masculinity/femininity, and individualism) of each country. Algebraically, this composite index is constructed as follows:

$$CD_{ij} = \sum_{c=1}^{4} \left\{ \left(I_{ci} - I_{cj} \right)^2 / V_c \right\} 4,$$

where I_{ci} stands for the host country i's cth cultural dimension, I_{cj} is the home country j's cth cultural dimension, j' is the variance of the cth dimension, V_c is the cultural distance index between the host country i and home country j. The cultural dimensions needed to construct this index are taken from Geert Hofstede's website at http://www.geerthofstede.nl/dimension-data-matrix.

No Former Colonial Relationship (*NoColony*)

We define an indicator of colony that takes the value of 1 if either the target nation was a colony of the acquirer nation, or vice-versa. For each pair of countries, we construct an indicator for *not* having a former (or current) colonial relationship as 1 minus the colony variable.

Religious distance (*ReligDist*)

We use information from the CIA Factbook on the fraction of population in a country assigned to one of the following religions: Catholic, protestant, Muslim, Buddhist, Hindu, Orthodox or Jewish. (https://www.cia.gov/library/publications/the-world-factbook/). We construct a common religion index between two countries by summing the products of population shares with the same religion; this leads to a continuous index between 0 and 1, and then define the religious distance variable as 1 minus the common religion index.

Labor-to-capital ratio by sector

We use information from the Bureau of Economic Analysis (BEA) on "full time equivalent employees by industry" as a measure of labor, and on "private non-residential fixed assets by industry (net stocks reported at fixed cost)" as a measure of capital. Both data series are reported using the BEA industry classification (about 104 industry codes), which has direct correspondance to a combination of 3-digit and 4-digit NAICS classification codes. We then use a concordance between NAICS and SIC classification codes that was used in Bahar (2018) to get the stock of capital and labor by 3-digit SIC industry and construct the labor-to-capital ratio. Importantly, this ratio is available for all manufacturing and non-manufacturing industries in our dataset, a sectoral coverage that standard sources such as the NBER-CES Manufacturing Industry Database does not provide.

References

Aizenman, J., Spiegel, M.M., 2006. Institutional efficiency, monitoring costs and the investment share of FDI. Rev. Int. Econ. 14 (4), 683–697.
Alfaro, L., Chanda, A., Kalemli-Ozcan, S., Sayek, S., 2004. FDI and economic growth: the role of local financial markets. J. Int. Econ. 64 (1), 89–112.
Anderson, S.P., De Palma, A., Thisse, J.F., 1992. Discrete choice theory of product differentiation. MIT Press.
Anderson, T., 2014. Operations of US affiliates of foreign companies. Survey Curr. Bus.. http://www.bea.gov/scb/pdf/2014/11%20November/1114_activities_of_u.s_affiliates_of_foreign_multinational_enterprises.pdf.
Bahar, D., 2018. The hardships of long distance relationships: time zone proximity and knowledge transmission within multinational firms. Soc. Sci. Res. Netw. (SSRN) Working Paper 2674682.
Barefoot, K.B., 2013. U.S. multinational companies: operations of US. parents and foreign affiliates in 2011. Survey Curr. Bus.. https://www.bea.gov/scb/pdf/2013/11%20November/1113_mnc.pdf.
Bénassy-Quéré, A., Coupet, M., Mayer, T., 2007. Institutional determinants of foreign direct investment. World Econ. 30 (5), 764–782.
Blonigen, B.A., 2015. Industrial policy and downstream export performance. Econ. J. 126 (595), 1635–1659.
Blonigen, B.A., Piger, J., 2014. Determinants of foreign direct investment. Canadian J. Econ. 47 (3), 775–812.
Chor, D., Manova, K., 2012. Off the cliff and back? Credit conditions and international trade during the global financial crisis. J. Int. Econ. 87 (1), 117–133.
Correia, S., Guimarães, P., Zylkin, T., 2019. PPMLHDFE: fast Poisson estimation with high-dimensional fixed effects. arXiv preprint arXiv: 1903.01690.
Davies, R.B., Desbordes, R., Ray, A., 2018. Greenfield versus merger and acquisition FDI: same wine, different bottles? Canadian J. Econ. 51 (4), 1151–1190.
Di Giovanni, J., 2005. What drives capital flows? The case of cross-border M&A activity and financial deepening. J. Int. Econ. 65 (1), 127–149.
Elrod, A.A., Lindberg, B.M., Morgan, E.T., 2013. Annual industry accounts: advance statistics on GDP by industry for 2012. Survey Curr. Bus.. http://www.bea.gov/scb/pdf/2013/05%20May/0513_annual_industry-accts-text.pdf.
Erel, I., Liao, R.C., Weisbach, M.S., 2012. Determinants of cross-border mergers and acquisitions. J. Finance 67 (3), 1045–1082.
Feliciano, Z.M., Sun, J., 2016. Foreign entry into US. service industry by takeovers and the creation of new firms. Contemp. Econ. Policy 34 (3), 500–512.
Habib, M., Zurawicki, L., 2002. Corruption and foreign direct investment. J. Int. Bus. Stud. 33 (2), 291–307.
Head, K., Ries, J., 2008. FDI as an outcome of the market for corporate control: theory and evidence. J. Int. Econ. 74 (1), 2–20.
Hijzen, A., Görg, H., Manchin, M., 2008. Cross-border mergers and acquisitions and the role of trade costs. Eu. Econ. Rev. 52 (5), 849–866.
Keller, W., Yeaple, S.R., 2013. The gravity of knowledge. Am. Econ. Rev. 103 (4), 1414–1444.
Kleinert, J., Toubal, F., 2013. Production versus distribution-oriented FDI. Rev. World Econ. 149 (3), 423–442.
Kogut, B., Singh, H., 1988. The effect of national culture on the choice of entry mode. J. Int. Bus. Stud. 19 (3), 411–432.
Krautheim, S., 2013. "Export-supporting FDI. Canadian J. Econ. 46 (4), 1571–1605.
Manova, K., 2008. Credit constraints, equity market liberalizations and international trade. J. Int. Econ. 76 (1), 33–47.
Melitz, J., Toubal, F., 2014. Native language, spoken language, translation and trade. J. Int. Econ. 93 (2), 351–363.
Oldenski, L., 2012. Export versus FDI and the communication of complex information. J. Int. Econ. 87 (2), 312–322.
Raimondi, V., Scoppola, M., 2018. Foreign land acquisitions and institutional distance. Land Econ. 94 (4), 517–540.
Rajan, R., Zingales, L., 1998. Financial development and growth. Am. Econ. Rev. 88 (3), 559–586.
Rossi, S., Volpin, P.F., 2004. Cross-country determinants of mergers and acquisitions. J. Financ. Econ. 74 (2), 277–304.
Stein, E., Daude, C., 2007. Longitude matters: time zones and the location of foreign direct investment. J. Int. Econ. 71 (1), 96–112.
United Nations Conference on Trade and Development (UNCTAD), 2015. World Investment Report: Reforming International Investment Governance. United Nations, Geneva and New York.