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Spatial outward FDI: Evidence from China's multinational firms

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Abstract

This paper studies the impacts of geographic proximity and investment connection on the outward foreign direct investment (OFDI) decisions by Chinese multinational firms, including both greenfield investment and cross-border merger and acquisition. We model firms' OFDI expansion with the lagged spatial structure, and collect outward FDI data of 3479 Chinese multinational firms from 2002 to 2013 whose investment destination covers more than 160 countries. We find that the spatial expansion of firms' existing OFDI play an important role in shaping their future investment decisions. Firstly, firms tends to invest in destinations that are closer to China, and expand further into destinations that are geographically closer to their existing OFDI locations. This is the geographic network effect. Secondly, we also find that firms are more likely to invest in countries with more intense FDI from China, and extend their OFDI networks to destinations with stronger investment connections with their existing subsidiary locations. This is the investment network effect. We show that these two effects are robust to alternative investment and geographic network measures and further controls.

KEYWORDS

China, multinational firms, outward foreign direct investment, spatial model

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1 | INTRODUCTION

China initiated her "go global" policy in 1999, joined World Trade Organization (WTO) in 2001, and signed more and more regional free trade and investment agreements such as the Belt and Road Initiative, RCEP and CAI in the past 10 years. Over the decades, the volume of China's outward foreign direct investment (OFDI) has been increasing at a tremendously fast speed. Starting from almost zero OFDI before 1980, the scale of China's OFDI ranked among top 10 in the world in 2015, and further reached to top 1 with 153.7 billion dollars in 2020, covering more than 80% of the countries in the world. Though China has experienced a rapid expansion of OFDI over the world, little is known how the past geographic and investment expansion of multinational firms, through the oversea destination countries, affect the subsidiary location choices of their OFDI, when they develop their global network. To fill the gap, we try to identify the impacts of the past geographic and investment expansion on the subsidiary global network of Chinese multinational firms in this paper.

The geographic expansion of a Chinese manufacturing firm specializing in sewing machine[1] in the global market serves as a very good example to illustrate the OFDI expansion of Chinese multinational firms, which motivates our study. In Figure 1, indicated by the solid black arrow, we find that the firm began its expansion in the Asian market by entering Hong Kong, China[2] in 1990. Then based on Hong Kong, China, the firm started to enter into Southeast Asian countries which are close to Hong Kong, China (indicated by the red dashed arrows): Singapore (2004), Cambodia (2006), Indonesia (2007), and Thailand (2007). Later, based on the four Southeast Asian countries, the firm conducted its further investment (indicated by the purple dotted arrow) towards South Asian area—India in 2008. Similarly, in 1997, the firm started its expansion in America by investing in the United States (indicated by the black solid arrow). Radiating from the United States in North America, the firm entered South American market by investing in Brazil in 2002 (indicated by the red dashed arrow). Sooner the expansion became deeper in the region (indicated by the purple dotted arrows) by entering Latin American countries: Mexico and Venezuela.

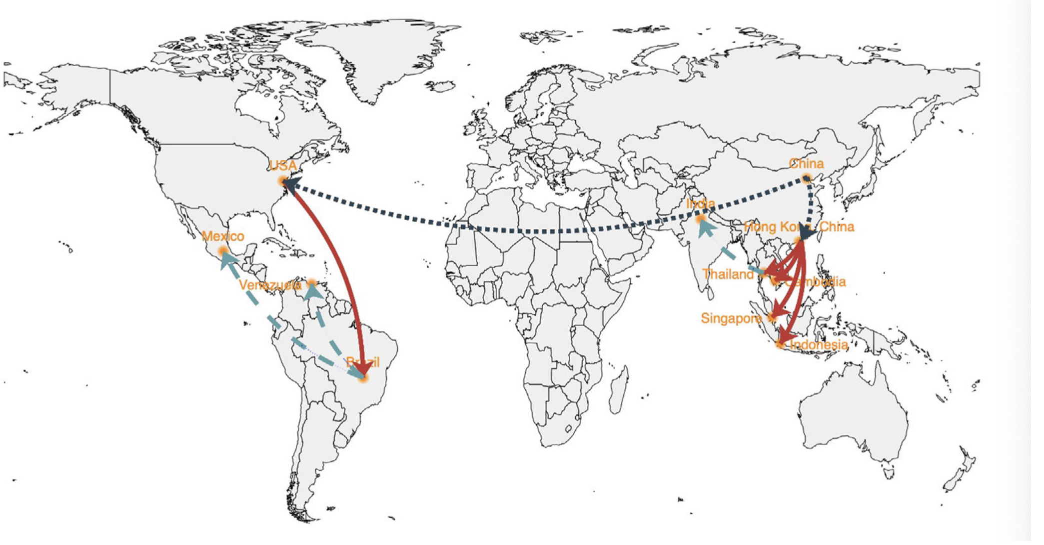

FIGURE 1 Geographic expansion of a Chinese manufacturing firm.

We collect OFDI data of 3479 Chinese multinational firms from 2002 to 2013. There are more than 160 OFDI destination countries for China. This dataset provides detailed OFDI records of Chinese firms at the extensive margin—including destination countries and transaction date. Furthermore, given that we have the full history of firms' location choices, we model firms' OFDI expansion with a lagged spatial structure. To fit the spatial model, we construct the geographic proximity variables on OFDI of any specific firm by using the past destinations' location information and the investment connection variables on OFDI of a firm by combining the past destinations with the bilateral FDI flows. Based on these two types of variables, we could possibly disentangle the geographic impact from the investment influence when a Chinese multinational firm seeks for global expansion.

To quantify the geographic impact, we consider two standard measures of geographic proximity: geographic distance and geographic network. The former is an absolute inverse geographic distance between China and its potential OFDI destination country c, generating the direct distance effect; and the latter is the sum of the inverse distances between a Chinese multinational firm's existing OFDI destination countries c's and its potential destination country c, inducing the indirect geographic network effect. We find that similar to imports and exports (Chaney, 2014), there exist sizable direct distance effect and indirect geographic network effect. That is, a Chinese multinational firm tends to choose a closer country to enter; and the firm has a higher propensity to conduct OFDI in the countries closer to its existing OFDI destination countries.

To quantify the investment influence, we consider two measures as well: investment intensity defined as the FDI flow from China to her potential OFDI destination country c, and investment network calculated as the sum of the bilateral FDI flows between a firm's existing OFDI destination countries c's and its potential destination country$c$. Similar to the geographic impacts, we also find the existence of both the direct investment effect induced by investment intensity and the indirect investment network effect from investment network. A Chinese multinational firm tends to invest in the country with a higher FDI intensity from China and enter the country with more FDI from the firms' existing OFDI destinations.

To the best of our knowledge, this paper is the first paper which simultaneously considers the impacts of both geographic proximity and investment connection on firm-level OFDI destination choices. First of all, we develop a set of estimation models that incorporate the spatial structure to discuss how the spatial structure in the existing OFDI expansion affect the future investment, and clarify the necessary conditions to achieve the identification.

Second, we confirm that the gravity property exists with respect to both the geographic distance and investment intensity.

Third, we find that if a multinational firm plans to invest in a potential destination country c, its existing past OFDI network can help to compensate country c's absolute distance disadvantage apart from China, and help to enhance the effect from the investment intensity from China to country c. That is, the closer the geographic distance and the more connected investment relationship between the countries on the existing network and the destination country, the more likely for a firm to enter the destination country.

Last, we show that the global expansion of OFDI is different from imports and exports. The historical network that takes into account all the past experience matters more than the intermediate network from just the last period. In particular, the cumulative past OFDI experience of a firm plays an important role in its future investment decision.

Our paper builds upon three streams of literature: spatial and sequential exporting and FDI, FDI location choice and information network.

Spatial and sequential exporting and FDI

Chaney (2014) develops an extended gravity model[3] to capture the direct and remote search effects in trade. That is, a firm tends to export to the country nearby and then uses the exported countries to start remote search to enter into other countries, which is also supported by Albornoz et al. (2012) and Defever et al. (2015). Head and Mayer (2019) finds that multinational firms in the car industry use their foreign affiliates as export platforms and prefer exporting to the markets close to the headquarters. Wang (2021) further finds that the affiliates of Chinese multinational firms of all industries bias their exports towards the markets close to China. Spatial interdependence plays a significant role in US outbound activity (Blonigen et al., 2007), and a Belgian firm chooses to test via exports before engaging FDI (Conconi et al., 2016). Our paper closely relates to Chaney (2014), where we try to test whether the direct distance effect and indirect network effect also exist when a firm conducts OFDI. Different from this strand of literature, we also identify the investment impact other than the geographic effect on OFDI, and find that both effects are prominent determinants of firms' OFDI decisions.

FDI location choice

What are the factors that attract more FDI? The factors are firm heterogeneity including cost structure and productivity (Aw & Lee, 2008; Chen & Moore, 2010), institutional factors (Aleksynska & Havrylchyk, 2013; Benassy-Quere et al., 2007; Du et al., 2008), taxation and salary (Mutti & Grubert, 2004), third-country competition (Eichengreen & Tong, 2007), stock and previous flow of investment (Blonigen et al., 2005) and agglomeration effect (Alfaro & Chen, 2014). In particular, Wei (2010) summarizes the literature on Chinese OFDI including the firm and country specific disadvantage and advantage of Chinese multinationals. Our paper focuses on the global expansion of a multinational firm dynamically; more specifically, how a multinational firm expands through self-learning.

Information network

The information network model is first proposed by Rauch (1999), where the information network is essential to break the information barrier in the trade, and the geographic proximity, through influencing the network structure, can increase the magnitude of trade. Besides international trade, this view has also been demonstrated in FDI studies. Chen and Chen (1998) uses Taiwanese firm-level data to consider the internal and external links of firms. They find that firms tend to use external links to start remote search when making FDI location Choice. Multinational firms prefer the region with lower information costs. Javorcika et al. (2011) studies the impact of the American immigrants ethnicity network on FDI choices. Chen (2011) investigates the effect of existing production networks on French multinationals' entry decisions by focusing on trade barriers (distance and tariff). Egger et al. (2014) sets up a network development model of multinational enterprises and find empirical supports from German multinationals that firms expand in markets that are closer to their home base and proceed step by step according to the correlated learning of the information of different markets. Our paper also builds on information network and examines how the existing geographic and investment network structures overcome the local information barriers of the countries closer to the existing network and lead to future investment in these countries.

The structure of our paper is organized as follows. Section 2 illustrates the OFDI data of Chinese multinational firms. Section 3 describes the estimation model specifications and the constructed variables. The empirical results are reported in Section 4. Section 5 conducts a few robustness checks. And Section 6 concludes.

2 | DATA

We describe the data and illustrate how Chinese multinational firms conducted OFDI and gradually expanded from 2002 and 2013 in this section.

2.1 | Databases

Our main analysis relies on three different data sources: the firm-level cross-border merger and acquisition from Zephyr, the greenfield data from the Ministry of Commerce of the People's Republic of China and other variables constructed from other databases.

The Zepher merger & acquisition database

Our analysis abstracts M&A data of domestic firms in China from Zepher database. This database has a long horizon but here we only choose the period from 2002 to 2013 to match the greenfield investment data from the Ministry of Commerce of the People's Republic of China. This database includes the detailed M&A information, like the nationality of acquirer and target firms, the announcement date and the closing date of the deal, and the transaction amount of M&A. Using this data, we are able to construct the M&A historical sequence for Chinese multinational firms.

The greenfield investment information

The greenfield investment data is drawn from the FDI administrative database from the website of Ministry of Commerce. This database reports the local information of the domestic firms, the nationality of target countries, and the conducting year of each OFDI. Similar to the M&A data, we could construct the greenfield historical sequential OFDI of Chinese multinational firms.

Other sources

Besides the two main databases above, we collect all other variables from the following databases. In particular, the geographic distance comes from CEPII (Centre d'Etudes Prospectives et d'Informations Internationales) database (Mayer & Zignago, 2006), which includes the distance between the capitals and the most populated cities of each country. CEPII also provides the common language information. We apply the ISO-3166 standard to define common region variable[4]. We use IMF World Economic Outlook database to compile the country-level GDP per capita data. We obtain the bilateral FDI data and the country code conversion table from IMF and WorldAtlas, respectively.

2.2 | Chinese OFDI preferred destinations

Table 1 reports the most preferred OFDI destinations of Chinese multinational firms.

Panel (a) of Table 1 gives the summary statistics of top 10 most favored greenfield investment destinations of Chinese multinational firms. It shows that 3365 domestic firms have ever completed greenfield investment more than once[5]. Among these firms, there are more than 28,000 transactions between 2002 and 2013. On average, each firm has about eight deals. The top two destinations are Hong Kong, China and USA. And Russia has gained its popularity since 2006 and ranks the third.

Panel (b) of Table 1 reports the summary statistics of top 10 most preferred cross-border M&A destinations of Chinese multinational firms.[6] The statistics shows that there are 152 Chinese multinational firms who have ever incurred cross-border M&A deals more than once.

TABLE 1 Top 10 OFDI destinations of Chinese multinational firms.

Country	2002–2005	2006–2010	2011–2013
Panel (a): Top 10 greenfield investment destinations			
Hong Kong, China	228	2511	5036
USA	132	1048	1842
Russia	107	567	462
Japan	46	413	363
Viet Nam	76	455	274
Australia	29	262	388
Germany	53	279	339
United Arab Emirates	52	374	241
Singapore	23	191	397
South Korea	37	317	251
Other	647	4614	6003
Panel (b): Top 10 cross-border M&A destinations			
Hong Kong, China	14	70	11
Australia	1	25	16
USA	6	10	26
Singapore	4	16	8
Canada	2	15	7
UK	1	9	14
Germany	3	3	10
France	3	3	6
Italy	1	6	1
Malaysia	0	6	2
Other	19	44	48

Note: Panel (a) shows the frequency of greenfield investments by Chinese multinational firms. There are 3365 Chinese multinationals conducting greenfield ODI more than once. Panel (b) shows the frequency of cross-border M&A activities by Chinese multinational firms. Cayman islands (CYM), Bermuda (BMU), and British Virgin Islands (VGB) are excluded. There are 152 Chinese multinationals conducting cross-border M&A more than once.

Among these firms, in total, 410 representative cross-border deals have been successfully completed and on average each firm has 2.7 deals. Regarding where the OFDI goes to through cross-border M&A, we find that Hong Kong, China, USA and Australia are among the top three destinations.

Over the time, we can see that both the greenfield OFDI and cross-border M&A of Chinese multinationals have kept on increasing. In Figure 2, we rank the countries according to the cumulative number of transactions by Chinese multinationals' OFDI from 2003 to 2012, and present OFDI country popularity using the quartile ranges. Chinese multinational firms prefer more developed markets such as USA, Canada, Australia, and European countries, as well as bigger market such as Brazil and India. Firm-level behaviors in China show a clear profit-seeking incentive just like the multinational firms from the advanced economies.

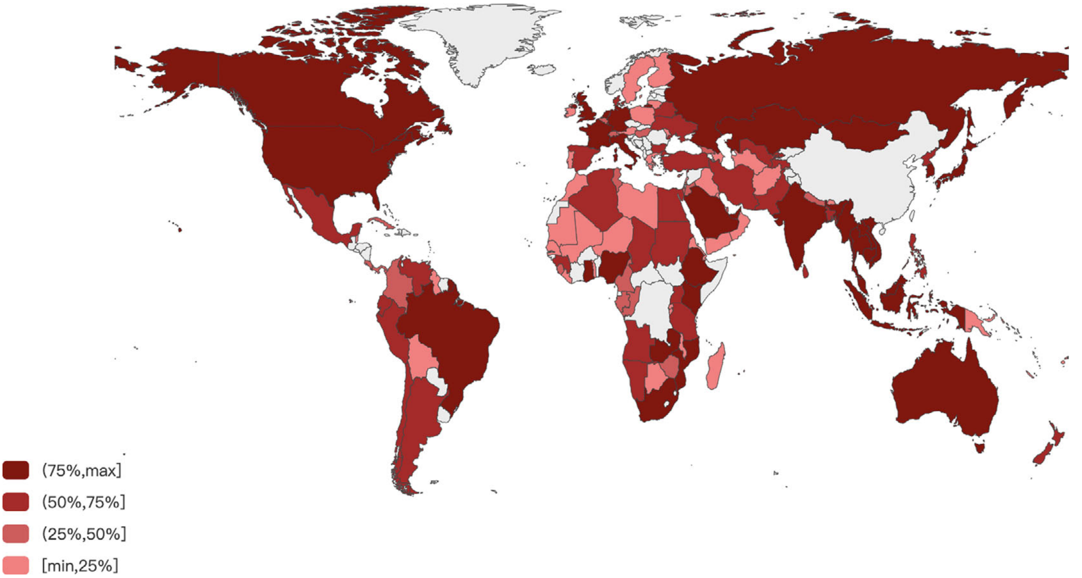

FIGURE 2 OFDI country popularity quartiles of Chinese multinational firms.

3 | ESTIMATION MODELS

The key research question in this paper is how Chinese multinationals firms expand at the extensive margin over the time by choosing their OFDI destinations.

3.1 | Main model specifications

We use the spatial model to examine how the immediate or historical OFDI network affects the later OFDI decision. Specifically, how the last period OFDI decision or the past OFDI decisions cumulatively affect the current period OFDI destination choice of a Chinese multinational firm. In particular, we consider the model with the spatial OFDI lags. Let $\underline{ODI}_{f,t} = \left(ODI_{f,1,t}, ODI_{f,2,t}, \dots, ODI_{f,c,t}, \dots, ODI_{f,C,t}\right)'$ denote the OFDI for firm f at time t and let $\underline{ODI}_{f,t-1} = \left(ODI_{f,1,t-1}, ODI_{f,2,t-1}, \dots, ODI_{f,c',t}, \dots, ODI_{f,C,t-1}\right)'$ denote the OFDI for firm f at time $t-1$. Note that we explicitly use c to denote the country where firm invests in the current period and use c' to denote the countries where the firm invests in the previous periods. The inverse distance weighting matrix as

$$W_{g(d_{cc'})} = \begin{bmatrix} g\left(d_{1,1}\right) & g\left(d_{1,2}\right) & \cdots & g\left(d_{1,c'}\right) & \cdots & g\left(d_{1,C}\right) \\ g\left(d_{2,1}\right) & \ddots & & & & g\left(d_{2,C}\right) \\ \vdots & & \ddots & & & \vdots \\ g\left(d_{c,1}\right) & & & g\left(d_{c,c'}\right) & & g\left(d_{c,C}\right) \\ \vdots & & & & \ddots & \vdots \\ g\left(d_{C,1}\right) & g\left(d_{C,2}\right) & & g\left(d_{C,c'}\right) & & g\left(d_{C,C}\right) \end{bmatrix}$$

in which $g(\cdot)$ a normalized inverse measure of geographic distance between two countries, taking the form $g(d) = 10{,}000/distance$ and the diagonal elements are zero, the FDI weighting matrix as

$$W_{FDI_{cc',t-1}} = \begin{bmatrix} FDI_{1,1,t-1} & FDI_{1,2,t-1} & \cdots & FDI_{1,c',t-1} & \cdots & FDI_{1,C,t-1} \\ FDI_{2,1,t-1} & \ddots & & & & FDI_{2,C,t-1} \\ \vdots & & \ddots & & & \vdots \\ FDI_{c,1,t-1} & & & FDI_{c,c',t-1} & & FDI_{c,C,t-1} \\ \vdots & & & & \ddots & \vdots \\ FDI_{C,1,t-1} & FDI_{C,2,t-1} & \cdots & FDI_{C,c',t-1} & & FDI_{C,C,t-1} \end{bmatrix}$$

in which $FDI_{c,c',t-1}$ a bilateral foreign direct investment flow (FDI) from country c' to country c at year $t-1$ and the diagonal elements are zero, the inverse distance as $\underline{g}(d_{CN}) = \left(g\left(d_{1,CN}\right), g(d_{2,CN}), \ldots, g(d_{c,CN}), \ldots, g(d_{C,CN})\right)'$, and $\underline{FDI}_{CN,t-1} = \left(FDI_{1,CN,t-1}, FDI_{2,CN,t-1}, \ldots, FDI_{c,CN,t-1}, \ldots, FDI_{C,CN,t-1})\right)'$, together with GDP per capita $\underline{GDPpc}_t = \left(GDPpc_{1,t}, GDPpc_{2,t}, \ldots, GDPpc_{c,t}, \ldots, GDPpc_{C,t})\right)'$, construct the variable set $X_{c,t}$. Moreover, in our setting, we define the last period firm-specific effective distance between country c and China as $\underline{Z}_{f,t-1} = \left(Z_{f,1,t-1}, Z_{f,2,t-1}, \ldots, Z_{f,c,t-1}, \ldots, Z_{f,C,t-1}\right)'$, in which $Z_{f,c,t-1} = g\left(d_{CN,c}\right) \times \mathbf{I}\left(ODI_{f,c,t-1} > 0\right)$ and $\mathbf{I}\left(ODI_{f,c,t-1} > 0\right)$ is defined below in equation (1), the firm fixed effect as d_f, and the year fixed effect as d_t. Last we define a $C \times 1$ vectore, ι as $\iota = (1, 1, \ldots, 1)'$.

Consider the latent ODI as

$$\begin{aligned} \underline{ODI}^*_{f,t} = {} & \alpha_1 \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \\ & + \beta_1 W_{g(d_{cc'})} \times \iota + \beta_2 \underline{g}\left(d_{CN}\right) + \beta_3 W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] \\ & + \gamma_1 W_{FDI_{cc',t-1}} \times \iota + \gamma_2 \underline{FDI}_{CN,t-1} + \gamma_3 W_{FDI_{cc',t-1}} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] \\ & + \eta \underline{GDPpc}_t + \delta \underline{Z}_{f,t-1} + d_f \times \iota + d_t \times \iota + \underline{\varepsilon}_{f,t} \end{aligned} \tag{1}$$

$$\mathbf{I}\left(\underline{ODI}_{f,t} > 0\right) = \begin{cases} 1 & \text{if } \underline{ODI}^*_{f,t} > 0 \\ 0 & \text{otherwise} \end{cases}$$

We denote the conditional distribution by $D\left(ODI_{f,c,t} | X_{c,t}, \underline{Z}_{f,t-1}, \underline{ODI}_{f,t-1}, d_f, d_t\right)$. Now we assume the following regularity conditions hold.

Assumption M (Model specification).

1. For $t = 1, 2, \ldots, T$, $D\left(ODI_{f,c,t} | X_{ct}, \underline{Z}_{f,t-1}, \underline{ODI}_{f,t-1}, d_f, d_t\right) = D\left(ODI_{f,c,t} | X_{c,t}, X_{c,t-1}, \ldots, X_{c,0}, \underline{Z}_{f,t-1}, \ldots, \underline{Z}_{f,0}, \underline{ODI}_{f,t-1}, \ldots, \underline{ODI}_{f,c,0}, d_f, d_t\right)$.
2. For $t = 1, 2, \ldots, T$, $D\left(ODI_{f,c,t} | X_{ct}, \underline{Z}_{f,t-1}, \underline{ODI}_{f,t-1}, d_f, d_t\right)$ is a correctly specified density for the conditional distribution on the left-hand side of equation.

This assumption suggests that at most one lag of $ODI_{f,c,t-1}$ and $\left(ODI_{f,1,t-1}, ODI_{f,2,t-1}, \dots, ODI_{f,c',t-1}, \dots, ODI_{f,C,t-1}\right)$ with $c' \neq c$ appeared in the distribution, which can be easily extended to allow for more lags in the regressors.

Assumption W (Weighting matrix).

1. (a) $W_{g(d_{cc'})}$ is a constant spatial weight matrix and its diagonal elements satisfy $w_{g(d_{cc'})} = 0$ for $c = 1, 2, \dots, C$.
   (b) $W_{FDI_{cc',t-1}}$ is a time-varying spatial weight matrix, and its diagonal elements satisfy $w_{FDI_{cc',t-1}} = 0$ for $c = 1, 2, \dots, C$.
2. $W_{g(d_{cc'})}$ and $W_{FDI_{cc',t-1}}$ are uniformly bounded in row and column sums in absolute value.

Assumption W.1 is a common assumption in the spatial model, which restricts the diagonal elements of the weighting matrix to equal to zero, like Yu et al. (2008). Assumption W.2 is a technique condition to ensure that the weighting matrix is well-defined.

Assumption E (Idiosyncratic error term).

1. The disturbance $\varepsilon_{f,c,t}, f = 1, 2, \dots, n, c = 1, 2, \dots, C$ and $t = 0, 1, \dots, T$ are i.i.d. across the firm f, country c and time t.
2. $\varepsilon_{f,c,t} \sim N(0, 1)$.

Assumption E assumes the idiosyncratic shocks are i.i.d. across firms, countries and time. This is a relatively strong assumption but common in the nonlinear panel model (Wooldridge, 2005). This condition is necessary for us to achieve identification later.

To address the initial conditions and incidental parameter problems, we adopt Wooldridge (2005) and Rabe-Hesketh and Skrondal (2013) to assume that the firm fixed effect is in a parametrized structure as in Assumption F[7] and can be added in the original estimation equation.

Assumption F (Fixed effects). $D\left(d_f | \underline{ODI}_{f,0}, Z_{f,c,t-1}, \dots, Z_{f,c,0}\right) = D(d_f | \underline{ODI}_{f,0}, X_{c,t}, X_{c,t-1}, \dots, X_{c,0}, Z_{f,c,t-1}, \dots, Z_{f,c,0}, d_t)$

$$\text{and } d_f | \underline{ODI}_{f,0}, Z_{f,c,t-1}, \dots, Z_{f,c,0} \sim N\left(\kappa_0 + \kappa_1 y_{f,0} + \kappa_2 \overline{Z}_f + \kappa_3 Z_{f,0}, \sigma^2_{\xi_f}\right)$$

where $y_{f,0}$ is the initial investment outcome across countries, which is defined as for $c = 1, 2, \dots, C$

$$y_{f,0} = \mathbf{I}\left(\mathbf{I}\left(ODI_{f,c,0} > 0\right) = 1, \text{for any } c\right),$$

$\overline{Z}_f$ is an average of (nonredundant) explanatory variables across countries and time, defined as for $c = 1, 2, \dots, C$ and $s = 1, 2, \dots T$,

$$\overline{Z}_f = \frac{1}{T}\frac{1}{C}\sum_{c=1}^{C}\sum_{s=1}^{T} Z_{f,c,s},$$

and $Z_{f,0}$ is an average of (nonredundant) explanatory variables at initial period $t = 0$, defined as for $c = 1, 2, \dots, C$

$$Z_{f,0} = \frac{1}{C}\sum_{c=1}^{C} Z_{f,c,0}.$$

In other words, Assumption F implies the folllowing fixed effect equation holds;

$$d_f = \kappa_0 + \kappa_1 y_{f,0} + \kappa_2 \overline{Z}_f + \kappa_3 Z_{f,0} + \xi_f.$$

Note that the regression variables[8] in our fixed effect equation are corresponding to the initial outcome variable, the average explanatory variable and the the initial explanatory variable in the specification of Rabe-Hesketh and Skrondal (2013). The only difference is that we average over the countries when defining these variables as we also have the variation across countries.

In our estimation, we first introduce the set of variables as defined in equation (1); secondly we add the variables $y_{f,0}, \overline{Z}_f$ and $Z_{f,0}$ in the regression equation to address the incidental parameters problems of the firm fixed effect issue; thirdly we use the year dummies to present the time fixed effect; and finally we apply the Probit model to estimate the coefficients.

Following Assumption F, we can write the latent ODI as

$$\begin{aligned}
\underline{ODI}^{*}_{f,t} = \alpha_1 \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \\
&+ \beta_1 W_{g(d_{cc'})} \times \iota + \beta_2 \underline{g}\,(d_{CN}) + \beta_3 W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] \\
&+ \gamma_1 W_{FDI_{cc',t-1}} \times \iota + \gamma_2 \underline{FDI}_{CN,t-1} + \gamma_3 W_{FDI_{cc',t-1}} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] \\
&+ \eta \underline{GDPpc}_t + \delta \underline{Z}_{f,t-1} + (\kappa_0 + \kappa_1 y_{f,0} + \kappa_2 \overline{Z}_f + \kappa_3 Z_{f,0}) \times \iota + d_t \times \iota + \xi_f \times \iota + \underline{\varepsilon}_{f,t}. \qquad (2)
\end{aligned}$$

Assumptions E and F give that

$$\xi_f + \varepsilon_{f,c,t} | \underline{ODI}_{f,0}, Z_{f,c,t-1}, \ldots, Z_{f,c,0} \sim N(0, \sigma^2_{\xi_f} + 1).$$

With $F(\cdot)$ is the CDF of normal distribution, it follows that

$$\begin{aligned}
\Pr\Big(\mathbf{I}\left(\underline{ODI}_{f,t} > 0\right)\ |X_{c,t}, \underline{Z}_{f,t-1}, \underline{ODI}_{f,t-1}, d_t\Big) \\
&= F_{\sigma^2_{\xi_f}+1}\Big(\alpha_1 \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \\
&+ \beta_1 W_{g(d_{cc'})} \times \iota + \beta_2 \underline{g}\,(d_{CN}) + \beta_3 W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] \\
&+ \gamma_1 W_{FDI_{cc',t-1}} \times \iota + \gamma_2 \underline{FDI}_{CN,t-1} + \gamma_3 W_{FDI_{cc',t-1}} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] \\
&+ \eta \underline{GDPpc}_t + \delta \underline{Z}_{f,t-1} + (\kappa_0 + \kappa_1 y_{f,0} + \kappa_2 \overline{Z}_f + \kappa_3 Z_{f,0}) \times \iota + d_t \times \iota\Big). \qquad (3)
\end{aligned}$$

Different from imports and exports data, OFDI data has the following features: (i) OFDI is typically less frequent than imports and exports at the firm level, so it is less likely to find the subsequent investment over two consecutive years; (ii) each OFDI transaction is a big investment decision for multinational firms. And therefore the historical network with the cumulative effect from all past experience (from 1 to $t - 1$) rather than the immediate network plays a more significant role in the decision. Like, firms takes time to use the network to obtain the knowledge of the regional politics, economy and culture. Therefore, we extend Assumption M in the historical network setup as the following equation[9] shows.

$$
\begin{aligned}
&\Pr(\mathbf{I}\left(\underline{ODI}_{f,t} > 0\right) | X_{c,t}, \dots, X_{c,1}, \underline{Z}_{f,t-1}, \underline{ODI}_{f,t-1}, \dots, \underline{ODI}_{f,1}, d_t)\\
&= F_{\sigma^2_{\xi_f}+1}\left(\alpha_1 \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \alpha_2 \mathbf{I}\left[\underline{ODI}_{f,t-2} > 0\right] + \dots + \alpha_{t-1}\mathbf{I}\left[\underline{ODI}_{f,1} > 0\right]\right.\\
&+ \beta_1 W_{g(d_{cc'})} \times \iota + \beta_2 \underline{g}(d_{CN}) + \beta_3 \sum_{s=1}^{t-1} W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,s} > 0\right]\\
&+ \gamma_1 \sum_{s=1}^{t-1} W_{FDI_{cc',s}} \times \iota + \gamma_2 \sum_{s=1}^{t-1} \underline{FDI}_{CN,s} + \gamma_3 \sum_{s=1}^{t-1} W_{FDI_{cc',s}} \times \mathbf{I}\left[\underline{ODI}_{f,s} > 0\right]\\
&\left.+ \eta \underline{GDPpc}_t + \delta \underline{Z}_{f,t-1} + (\kappa_0 + \kappa_1 y_{f,0} + \kappa_2 \overline{Z}_f + \kappa_3 Z_{f,0}) \times \iota + d_t \times \iota\right).
\end{aligned} \tag{4}
$$

Denote $\boldsymbol{\theta} = (\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ and $\hat{\boldsymbol{\theta}}_{probit}$ is the estimate from the probit model. Equations (3) and (4) suggest that

$$\hat{\boldsymbol{\theta}}_{probit} = \left(\sigma^2_{\xi_f} + 1\right)^{-1/2} \boldsymbol{\theta}.$$

We would like to highlight two issues in order to interpret our results. First, in the discrete choice model, like probit and logit model, parameters can be only identified up to scale. In the conventional setting, the coefficient is estimated relatively to the variation of the idiosyncratic error term, which is normalized to 1. Second, similar to the standard probit model as we explain above, we can only interpret the coefficients in a relative sense, but not in an absolute sense, that is, $\hat{\boldsymbol{\theta}}^{k}/\hat{\boldsymbol{\theta}}^{k'}$ with $\boldsymbol{k}, \boldsymbol{k'} \in (\alpha_1, \boldsymbol{\beta}, \boldsymbol{\gamma})$. Our estimates could provide a suggestive evidence on how the immediate and historical OFDI networks affect the later OFDI decision through the geographic proximity and investment connection.

3.2 | Construction of key variables

We define and construct all the key variables that allow us to further estimate Equations (3) and (4), discuss the economic implications of the coefficients of the these variables, and show the summary statistics.

3.2.1 | Dependent variable

The key dependent variable $\mathbf{I}[ODI_{f,c,t} > 0]$ is an indicator variable whether a Chinese firm f makes OFDI in country c in year t, which is equal to 1 if firm f has OFDI to country c at year t; otherwise it is equal to 0.

3.2.2 | Explanatory variables

The conditional probability that firm f will invest in country c at year t depends on two sets of factors (key independent variables): geographic proximity ($\boldsymbol{\beta}$) and investment connection ($\boldsymbol{\gamma}$).

Geographic proximity:

Three variables are constructed as in Equations (3) and (4): geographic position (β_1), geographic distance (β_2), and geographic network (β_3).

Geographic proximity :

	Immediate network	Historical network
Geographic position	$\sum_{c' \neq CN} g(d_{c,c'})$	$\sum_{c' \neq CN} g(d_{c,c'})$
Geographic distance	$g(d_{c,CN})$	$g(d_{c,CN})$
Geographic network	$\sum_{c' \neq c} g(d_{c,c'})\mathbf{I}[ODI_{f,c',t-1} > 0]$	$\sum_{c' \neq c} \sum_{s=1}^{t-1} g(d_{c,c'})\mathbf{I}[ODI_{f,c',s} > 0]$

Note that geographic position variable and geographic distance variable do not vary over time, and therefore they share the same definitions under the immediate network and historical network structures.

Geographic position reflects the relative location of the potential destination country c to the rest of the world other than China. Geographic distance is an inverse measure of distance between China and the potential destination country c which has a geographic direct distance effect on a Chinese multinational firm's OFDI. Geographic network is defined as the sum of the inverse distances of a Chinese multinational firm's previous OFDI destination country c''s (other than country c) in last year $t-1$ and the potential destination country c under the immediate network structure, and as the sum of the inverse distances of a Chinese multinational firm's previous OFDI destination country c''s (other than country c) in all past years from 1 to $t-1$ and the potential destination country c under the historical network structure; geographic network leads to an indirect geographic network effect on Chinese multinationals' OFDI, from all existing OFDI destination country c''s (other than country c) to the potential destination country c.

The coefficients $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3)$ represent the impacts of the geographic proximity. The coefficient β_1 measures the impact of geographic position of country c away from all countries other than China. Since $g(d)$ is an inverse measure of geographic distance, a negative β_1 means if country c locates closer to other countries but not China, it is the less likely for Chinese multinationals to conduct OFDI in it. The coefficient β_2 measures the direct impact of distance on OFDI. A **positive** β_2 suggests the geographic distance deters a Chinese multinational firm's OFDI entry, that is, a firm has a higher propensity to enter a nearby country than a remote one. This is referred to **"direct distance effect"** in our paper. The coefficient β_3 controls for the indirect impact of geographic network on OFDI. A **positive**β_3 suggests that if a firm has ever invested in countries c''s that are close to country c in year $t-1$ or in all past years from 1 to t-1, the more likely the firm will sequentially enter country c in year t. This is defined as **"geographic network effect"**.

Investment connection: Three variables are constructed as in Equations (3) and (4): investment attraction (γ_1), investment intensity (γ_2), and investment network (γ_3).

Investment connection :

Investment attraction	$\sum_{c' \neq CN} FDI_{c,c',t-1}$	$\sum_{c' \neq CN} \sum_{s=1}^{t-1} FDI_{c,c',s}$
Investment intensity	$FDI_{c,CN,t-1}$	$\sum_{s=1}^{t-1} FDI_{c,CN,s}$
Investment network	$\sum_{c' \neq c} FDI_{c,c',t-1}\mathbf{I}[ODI_{f,c',t-1} > 0]$	$\sum_{c' \neq c} \sum_{s=1}^{t-1} FDI_{c,c',s}\mathbf{I}[ODI_{f,c',s} > 0]$

Investment attraction is the total FDI flow the potential destination country c received in the last period $t-1$ from the rest of the world other than China under the immediate network structure, and is the cumulative total FDI flow from the the rest of the world other than China from 0 to $t-1$ under the historical network structure. Investment intensity is the FDI flow from China to the potential destination country c in the last period $t-1$ and in all past periods from 1 to $t-1$ under the immediate and historical network structure respectively. Similarly, investment network is defined as the total FDI flow from a Chinese multinational firm's previous OFDI destination country c''s (other than country c) to the potential destination country c in the last year $t-1$ under the immediate network structure and cumulatively in all past years from 0 to $t-1$ under the historical network structure.

There is a concern for the investment connection variables that the bilateral FDI flows may be affected by the geographic distance we use to define the geographic proximity variables. In order to disentangle the investment impacts from the geographic effects, we construct a purged FDI flow variable between any country pairs by running the gravity equation of bilateral FDI flows on the GDP of the two countries and the geographic distance between them and then taking the residuals from the estimation equation[10]. The purged FDI flows (the residuals) are applied as $FDI_{c,c',s}$, $s = 1, 2, \ldots, t-1$ in the definitions of investment connection variables[11].

Analogously to geographic effects $\boldsymbol{\beta}$'s, the coefficients $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \gamma_3)$ control for the influence of the investment connection. The coefficient γ_1 reveals the impact of investment attraction. A positive γ_1 implies that the more FDI from the rest of the world (other than China) a country attracts, the more likely a Chinese multinational firm will invest in the country. The coefficient γ_2 represents the direct impact of investment intensity on OFDI. A **positive**γ_2 suggests that a firm is more likely to invest the country having more FDI transactions with China, which we call it **"direct investment effect"**. The coefficient γ_3 captures the indirect impact of investment network on OFDI. The sign of the coefficient γ_3 **is expected to be positive**, which is defined as **"investment network effect"**. If a firm has ever invested in the countries that conduct more FDI in country c in year $t-1$ or in the past years from 0 to t-1, the more likely the firm will sequentially enter country c due to the similarity of investment and the economic relationship from their business partners in country c''s.[12]

Other variables:

We also include the last period firm-level OFDI decision $\mathbf{I}[ODI_{f,c,t-1} > 0]$ under the immediate network structure and all past periods firm-level OFDI decisions $\mathbf{I}[ODI_{f,c,s} > 0]$ for $s = 0, 1, \ldots t-1$ under the historical network structure, as well as a country-time level control variable $GDPpc_{c,t}$.

The coefficient α_1 in Equation (3) and $\boldsymbol{\alpha} = \alpha_1, \alpha_2, \ldots, \alpha_{t-1}$ in Equation (4) show the impact of a firm's past OFDI activities on the potential destination country c, which are believed to be positive since a firm is more likely to reinvest in a country that it had OFDI experience in the past. The coefficient η controls for the effect of the country-time level attribute (GDP per capita) on OFDI, which is also expected to be positive because a country with better economic development attracts more OFDI from China.

3.2.3 | Summary statistics

Panel (a) of Table 2 shows the summary statistics for the set of immediate network variables, while panel (b) shows shows the summary statistics for the set of historical network variables, together with panel (c) that lists the potential destination country c's GDP per capita in year t, we can get an overview of all the constructed variables.

On average, the probability of a Chinese multinational firm to conduct OFDI in a specific country c in year t is 0.2%, which is the key dependent variable in all the model specifications. As to geographic distance, the closest OFDI destination from China is less than 800 kilometers (10,000/12.353), while the farthest is more than 19,000 kilometers (10,000/0.518), the average distance between China and country c is a little more than 6000 kilometers (10,000/1.655). The

TABLE 2 Summary statistics.

	Unit	Max	Min	Median	Mean	SD
Panel (a): Immediate network						
Geo. Position $\sum_{c' \neq CN} g(d_{c,c'})$	10,000/km	1038.383	153.522	366.35	384.87	139.38
Geo. Distance $g(d_{c,CN})$	10,000/km	12.353	0.518	1.237	1.655	1.606
Geo. Network $\sum_{c' \neq c} \mathbf{I}[ODI_{f,c',t-1} > 0] g(d_{c,c'})$	10,000/km	425.106	0	2.463	5.104	11.523
Invest. Attraction $\sum_{c' \neq CN} FDI_{c,c',t-1}$	trillion \$	0.423	−0.045	0.00036	0.0083	0.027
Invest. Intensity $FDI_{c,CN,t-1}$	trillion \$	51.24	−0.815	0.00065	0.190	2.152
Invest. Network $\sum_{c' \neq c} \mathbf{I}[ODI_{f,c',t-1} > 0] FDI_{c,c',t-1}$	trillion \$	0.301	−0.061	0	0.0005	0.0038
Invest. Attraction (Purged)	trillion \$	396.7	−70.39	−0.294	1.704	21.75
Invest. Intensity (Purged)	trillion \$	50.33	−1.898	0	−0.021	2.121
Invest. Network (Purged)	trillion \$	0.293	−0.063	0	0.00032	0.0036
Panel (b): Historical network						
Geo. Position $\sum_{c' \neq CN} g(d_{c,c'})$	10,000/km	1038.383	153.522	366.35	384.87	139.38
Geo. Distance $g(d_{c,CN})$	10,000/km	12.353	0.518	1.237	1.655	1.606
Geo. Network $\sum_{c' \neq c} \sum_{s=1}^{t-1} \mathbf{I}[ODI_{f,c',s} > 0] g(d_{c',c})$	10,000/km	2303.747	0	2.954	6.264	16.042
Invest. Attraction $\sum_{c' \neq CN} \sum_{s=1}^{t-1} FDI_{c,c',s}$	trillion \$	59.8611	−6.7371	0.05	1.1499	3.8571
Invest. Intensity $\sum_{s=1}^{t-1} FDI_{c,CN,s}$	trillion \$	227.5	−0.0467	0.003	0.6195	8.052
Invest. Network $\sum_{c' \neq c} \sum_{s=1}^{t-1} \mathbf{I}[ODI_{f,c',s} > 0] FDI_{c,c',s}$	trillion \$	662.8	−111.4	0	0.219	2.962
Invest. Attraction (Purged)	trillion \$	1284	−161.1	−0.886	9.092	106.8
Invest. Intensity (Purged)	trillion \$	219.7	−10.35	0	−0.312	7.854
Invest. Network (Purged)	trillion \$	0.651	−0.114	0	0.00014	0.0028
Panel (c): Firm and country-level variables						
ODI Dummy at t $\mathbf{I}\left(ODI_{f,c,t} > 0\right)$		1	0	0	0.002	0.037
GDP per capita $GDP_{c,t}$	million \$	0.1148	0.0001	0.0038	0.0116	0.0172

Note: The above variables are defined in Section 3.2. The three purged investment connection variables use the residuals from the gravity estimation of FDI flows as in Appendix A instead of the original values of FDI flows.

sum of annual FDI flows from China to country c's on average is 190 billion dollars (0.190 trillion dollars). Since the investment connection measures are based on the FDI flow information, the variables could be negative if the withdrawal of FDI from country c in year $t-1$ is greater than the investment. The purged investment connection variables are also reported which are constructed by taking the residuals from the gravity model regression, and overall these purged variables have larger ranges with median (and mean) at around zero.

All the historical sequence adjusted variables under the historical network structure which consider the cumulative investment information over the time are larger than those under the immediate network structure, including geographic network, investment attraction, investment intensity, and investment network.

3.3 | Extended model specifications

In the main model specifications, we assume that the potential destination markets are independent. That is, each year when a firm makes decision, it only considers the past investment feature, is not forward-looking and thus will not make strategic joint investment decision over a particular region. Note that it is possible that a firm may sequentially enter a particular set of countries which have similar features, for instance, locating in a common economic region or sharing a common language. This may invalidate Assumption E and threat the identification.

We further ask whether the network effects, regardless of geographic or investment, are largely driven by some common features among the existing destination countries c''s and the potential destination country c. To alleviate these potential effects, we consider common region and common language as proxies for any possible regional and/or cultural expansion strategies of a multinational firm, and extend our analysis by introducing common region and common language effects into our network definitions as we show in the following extended model specifications.

Extended model specifications

$$
\begin{aligned}
&\Pr(\mathbf{I}\left(\underline{ODI}_{f,t}>0\right)|X_{c,t},\underline{Z}_{f,t-1},\underline{ODI}_{f,t-1},d_t\Big)\\
&=F_{\sigma^2_{\xi_f}+1}\Big(\alpha_1\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]+\\
&+\beta_1 W_{g(d_{cc'})}\times\iota+\beta_2\underline{g}(d_{CN})+\beta_3 W_{g(d_{cc'})}\times\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]\\
&+\beta_4 W_{g(d_{cc'}),R}\times\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]+\beta_5 W_{g(d_{cc'}),L}\times\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]\\
&+\gamma_1 W_{FDI_{cc',t-1}}\times\iota+\gamma_2\underline{FDI}_{CN,t-1}+\gamma_3 W_{FDI_{cc',t-1}}\times\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]\\
&+\gamma_4 W_{FDI_{cc',R,t-1}}\times\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]+\gamma_5 W_{FDI_{cc',L,t-1}}\times\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]\\
&+\eta\underline{GDPpc}_t+\delta\underline{Z}_{f,t-1}+(\kappa_0+\kappa_1 y_{f,0}+\kappa_2\overline{Z}_f+\kappa_3 Z_{f,0})\times\iota+d_t\times\iota\Big).
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
&\Pr(\mathbf{I}\left(\underline{ODI}_{f,t}>0\right)|X_{c,t},\ldots,X_{c,1},\underline{Z}_{f,t-1},\underline{ODI}_{f,t-1},\ldots,\underline{ODI}_{f,1},d_t\Big)\\
&=F_{\sigma^2_{\xi_f}+1}\Big(\alpha_1\mathbf{I}\left[\underline{ODI}_{f,t-1}>0\right]+\alpha_2\mathbf{I}\left[\underline{ODI}_{f,t-2}>0\right]+\ldots+\alpha_{t-1}\mathbf{I}\left[\underline{ODI}_{f,1}>0\right]
\end{aligned}
$$

$$+\beta_1 W_{g(d_{cc'})}\times\iota+\beta_2\underline{g}\left(d_{CN}\right)+\beta_3\sum_{s=1}^{t-1}W_{g(d_{cc'})}\times\mathbf{I}\left[\underline{ODI}_{f,s}>0\right]$$
$$+\beta_4\sum_{s=1}^{t-1}W_{g(d_{cc'}),R}\times\mathbf{I}\left[\underline{ODI}_{f,s}>0\right]+\beta_5\sum_{s=1}^{t-1}W_{g(d_{cc'}),L}\times\mathbf{I}\left[\underline{ODI}_{f,s}>0\right]$$
$$+\gamma_1\sum_{s=1}^{t-1}W_{FDI_{cc',s}}\times\iota+\gamma_2\sum_{s=1}^{t-1}\underline{FDI}_{CN,s}+\gamma_3\sum_{s=1}^{t-1}W_{FDI_{cc',s}}\times\mathbf{I}\left[\underline{ODI}_{f,s}>0\right]$$
$$+\gamma_4\sum_{s=1}^{t-1}W_{FDI_{cc',R,s}}\times\mathbf{I}\left[\underline{ODI}_{f,s}>0\right]+\gamma_5\sum_{s=1}^{t-1}W_{FDI_{cc',L,s}}\times\mathbf{I}\left[\underline{ODI}_{f,s}>0\right]$$
$$+\eta\underline{GDPpc}_t+\delta\underline{Z}_{f,t-1}+(\kappa_0+\kappa_1 y_{f,0}+\kappa_2\overline{Z}_f+\kappa_3 Z_{f,0})\times\iota+d_t\times\iota\Big). \tag{6}$$

Equations (5) and (6) show the extended model specifications under the immediate network and historical network structures respectively. In each specification, we generate two additional geographic network variables—geographic common region network and geographic common language network with coefficients β_4 and β_5, and two additional investment network variables—investment common region network and investment common language variable with coefficients γ_4 and γ_5. Four additional weighting matrices are defined in Appendix B, in which $W_{g(d_{cc'}),R}$ and $W_{FDI_{cc',R,s}}$ only consider the inverse distance and bilateral FDI flow if country c and c' are located in the same economic region, while $W_{g(d_{cc'}),L}$ and $W_{FDI_{cc',L,s}}$ only take into account the inverse distance and bilateral FDI flow if the two countries share the same language.

If it were the multinational firm's regional and cultural strategies that play the most important roles in its global network expansion, we would lose the statistic and economic significance of the coefficients β_3 and γ_3 by controlling these two effects. Otherwise, the geographic and investment network effects on the sequential global expansion do exist for a Chinese multinational firm.

4 | EMPIRICAL RESULTS

4.1 | Main specifications

Table 3 reports the regression results for the main model specifications under the historical network structure, as well as the immediate network structure.

Columns (1) and (2) show the immediate network structure results of Equation (3). We find that there indeed exist geographic proximity effects on a multinational firm's OFDI decision. First, the coefficient β_2 on the geographic distance reflects the direct distance effect. It is positive and significantly different from zero at the 1% level, meaning that the closer to China, it is more likely for a Chinese multinational to invest in that country. Second, the coefficient β_3 reflects the geographic network effect. It is positive and significant, suggesting that if a firm invested in the country c''s that are closer to country c or it invested in more country c''s given the distance between country c''s and c, it is more likely to enter country c sequentially. Last, as in column (2), β_3 (indirect geographic network effect) is about one fifth of β_2 (direct distance effect) in magnitude, which means that if a firm invests in one more country c' (apart from the same distance as China to the

TABLE 3 Main specifications (purged FDI flows): Probit regressions.

	Dependent variable: $y = 1[ODI_{f,c,t} > 0]$			
	Immediate network		**Historical network**	
	(1)	**(2)**	**(3)**	**(4)**
ODI Dummy at $t-1$	0.983***	0.924***	0.995***	0.928***
	(0.023)	(0.023)	(0.023)	(0.023)
Geo. Position	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Geo. Distance	0.029***	0.045***	0.041***	0.053***
	(0.001)	(0.002)	(0.002)	(0.002)
Geo. Network	0.006***	0.009***	0.002***	0.006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invest. Attraction	0.004***	0.003***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.00001)	(0.00002)
Invest. Intensity	0.031***	0.027***	0.007***	0.006***
	(0.0004)	(0.0004)	(0.0001)	(0.0001)
Invest. Network	0.043	1.717***	2.286***	4.205***
	(0.451)	(0.475)	(0.617)	(0.635)
GDP per capita		6.036***		5.700***
		(0.163)		(0.167)
ODI dummies from 0 to $t-2$	— No —		— Yes —	
Parameterized Firm FE with $y_0, Z_0, \overline{Z}$	— Yes —			
Year FE	— Yes —			
No. of Obs.	6,370,716	6,166,104	6,370,716	6,166,104
No. of Firms	— 3468 —			
No. of Countries	— 167 —			
No. of Years	— 11 —			
Pseudo R^2	0.138	0.152	0.122	0.141
Log Likelihood	−66,019.000	−63,898.250	−66,092.190	−63,658.330
Akaike Inf. Crit.	132,080.000	127,840.500	132,242.400	127,376.700

Note: All variable are defined in Section 3.2. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. Missing observations in column (2) and (4) are due to the lack of data of the country-level variable for some year-country pairs.

potential destination country c), it could compensate 20% of the distance disadvantage between country c and China.

Analogously, we find that there also exist investment connection effects on OFDI. The coefficient γ_2 represents the direct investment effect from investment intensity. It is positive and significantly different from zero at the 1% level, meaning that the more intensive China conducts outward FDI in a country, the more likely a Chinese firm will invest in the country. The coefficient γ_3 which represents the investment network effect is also positive and significant if we include GDP per capita control in column (2). Note that γ_3 (indirect investment network effect) is much larger in magnitude than γ_2 (direct investment effect), implying that if a firm plans to enter the market of country *c*, it is more effective by investing in more country c''s which have strong bilateral FDI relationship with the potential destination country *c* than relying on the increase in China's FDI flow to country *c*. An active global expansion strategy of a multinational firm is more influential than the macro FDI relationship between China and the potential destination country *c*.

Columns (3) and (4) of Table 3 report the estimates under the historical network. Similarly, the estimates of the coefficients remain the same as the immediate network setup as to the statistical significance. The effect from investment network relative to investment intensity gets much stronger in economic magnitude under the historical network, though the relative effect of geographic network is little weaker. Different from the geographic network, the investment network exists an over-time cumulatively enhancing effect, and therefore a well-planned long-term active global expansion strategy is even more important for any multinational firm.

4.2 | Extended specifications

Table 4 presents the estimates when we include the common region and the common language under both the immediate network (columns (1) and (2)) and the historical network (columns (3) and (4)).

The estimates on the geographic common region network are negative and significantly different from zero at the 1% level in all the specifications. A firm is less likely to enter multiple countries in the same economic region to avoid the self-competition effect. The estimates on the geographic common language network are consistently positive and significant. If a potential OFDI destination country shares the same language as the existing OFDI destinations, it may reduce the culture and information barriers for Chinese multinationals to enter.

Similar effects show up for the investment common region network and the investment common language network. Higher bilateral FDI flows from China to the existing OFDI destination countries make Chinese multinationals less likely enter a country in the same economic region, while such higher bilateral FDI flows encourage Chinese multinationals to invest in a country sharing the same language as their existing OFDI destinations.

These results suggest that a Chinese multinational firm does have some regional and cultural strategy to develop its global network.

Under the extended specifications, the coefficients of the geographic and investment network effects (β_3 and γ_3) under the historical network structure do not change much in either statistical significance or economic magnitude. Only the coefficient of the investment network under the immediate network structure loses the significance. In short run, the effect from the last-period investment network may be taken away by the regional and cultural strategies captured by the common region and common language. However, in the long run, the past cumulative OFDI experience adds extra effects on the sequential expansion of a Chinese multinational firm in addition to the existence of the regional and cultural strategies.

TABLE 4 Extended specifications (purged FDI flows): Probit regressions.

	Dependent variable: $y = 1[ODI_{f,c,t} > 0]$			
	Immediate network		**Historical network**	
	(1)	**(2)**	**(3)**	**(4)**
ODI dummy at $t-1$	0.958***	0.917***	0.966***	0.926***
	(0.023)	(0.023)	(0.023)	(0.023)
Geo. Position	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Geo. Distance	0.035***	0.048***	0.043***	0.055***
	(0.002)	(0.002)	(0.002)	(0.002)
Geo. Network	0.009***	0.009***	0.008***	0.008***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Geo. Common Region	−0.006***	−0.002***	−0.007***	−0.003***
	(0.0003)	(0.0004)	(0.0002)	(0.0003)
Geo. Common Lang.	0.009***	0.006*	0.005***	0.001***
	(0.0005)	(0.001)	(0.0004)	(0.0004)
Invest. Attraction	0.004***	0.003*	0.001***	0.001***
	(0.0001)	(0.0001)	(0.00001)	(0.00002)
Invest. Intensity	0.031***	0.027***	0.007***	0.006***
	(0.0004)	(0.0004)	(0.0001)	(0.0001)
Invest. Network	−0.032	0.967	2.523***	3.595***
	(0.599)	(0.637)	(0.857)	(0.872)
Invest. Common Region	−11.238***	−11.424***	−7.681***	−9.606***
	(1.288)	(1.288)	(1.742)	(1.719)
Invest. Common Lang.	6.679***	6.038***	3.039**	4.452***
	(1.000)	(1.030)	(1.329)	(1.328)
GDP per capita		5.975***		5.731***
		(0.164)		(0.167)
ODI dummies from 0 to $t-2$	— No —		— Yes —	
Parameterized Firm FE with $y_0, Z_0, \overline{Z}$	— Yes —			
Year FE	— Yes —			
No. of Obs.	6,370,716	6,166,104	6,370,716	6,166,104
No. of Firms	— 3468 —			
No. of Countries	— 167 —			
No. of Years	— 11 —			
Pseudo R^2	0.1143	0.154	0.130	0.142
Log Likelihood	−65,600.170	−63,765.570	−65,462.180	−63,594.440
Akaike Inf. Crit.	131,250.300	127,583.100	130,990.400	127,256.900

Note: All variable are defined in Section 3.2, 3.3 and Appendix B. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. Missing observations in column (2) and (4) are due to the lack of data of the country-level variable for some year-country pairs.

5 | ROBUSTNESS CHECKS

Besides the main and extended specifications, we also conduct the following robustness checks. First, we apply the original values of bilateral FDI flows instead of the purged ones to construct the investment connection variables. Second, we replace the purged bilateral FDI flows with the purged FDI stocks. Third, we add the country fixed effects and drop geographic position and geographic distance which only vary at the country level. The estimation results are similar as those in the main specifications. Below, we briefly discuss the robustness checks one by one.

5.1 | Original values of FDI flows

Throughout our main specifications and the extended specifications, we apply the purged FDI flows which are the residuals taken from the FDI gravity equation estimation. According to the summary statistics in Table 2, the purged FDI flows vary more than the original values of FDI flows. We use the original values of FDI flows to construct the three investment connection variables and show the regression results in Table 5, with columns (1) and (2) under the immediate network and columns (3) and (4) under the historical network.

Not surprisingly, the coefficients of geographic proximity variables are almost the same for both statistical significance and economic magnitude as the results from our main specifications. The coefficients of investment network are much larger in magnitude due to smaller variations of the original values of FDl flows, but lose the significance when we control for GDP per capita of the potential destination country, which provides some evidence that the original values of FDI flows are highly affected by the economic development as well as the geographic distance.

5.2 | Purged FDI stocks

Here we use a different measure for FDI, the purged FDI stocks instead of the purged FDI flows, to redefine investment attraction, investment intensity and investment network[13]. We expect that the results still hold by using the purged FDI stocks.

Table 6 reports the estimates under the immediate network (columns (1) and (2)) and historical network (columns (3) and (4)). We find that the statistical significance pattern is the same as the main specifications. In terms of economic magnitude, only the estimates on the investment connection variables are smaller than those with purged FDI flows. All other estimates are almost the same as the main specifications in Table 3.

5.3 | Country fixed effect

As a final check, we include country fixed effects besides the year fixed effects and firm fixed effects in our regressions, and therefore we automatically drop geographic position and geographic distance which only vary at the country level. However, the two most interesting variables—geographic network and investment network—which vary at the firm-country-year level will still show their effects.

TABLE 5 Robustness check 1: Original values of FDI flows (probit regressions).

	Dependent variable: $y = 1[ODI_{f,c,t} > 0]$			
	Immediate network		**Historical network**	
	(1)	**(2)**	**(3)**	**(4)**
ODI Dummy at $t-1$	0.882***	0.855***	0.919***	0.872***
	(0.024)	(0.024)	(0.023)	(0.023)
Geo. Positon	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Geo. Distance	0.049***	0.053***	0.052***	0.051***
	(0.002)	(0.002)	(0.002)	(0.002)
Geo. Network	0.006***	0.008***	0.002***	0.007***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Invest. Attraction	4.128***	3.513***	29.927***	25.488***
	(0.060)	(0.070)	(0.432)	(0.498)
Invest. Intensity	21.791***	20.962***	63.240***	61.092***
	(0.431)	(0.434)	(1.165)	(1.177)
Invest. Network	2.765**	1.439	31.548***	15.927
	(1.251)	(1.299)	(10.894)	(11.610)
GDP per capita		3.340***		3.641***
		(0.191)		(0.178)
ODI dummies from 0 to $t-2$	— No —		— Yes —	
Parameterized Firm FE with $y_0, Z_0, \overline{Z}$	— Yes —			
Year FE	— Yes —			
No. of Obs.	4,933,976	4,887,937	5,417,016	5,364,996
No. of Firms	— 3468 —			
No. of Countries	— 167 —			
No. of Years	— 11 —			
Pseudo R^2	0.161	0.167	0.136	0.149
Log Likelihood	−56,097.040	−55,256.930	−62,725.480	−61,285.350
Akaike Inf. Crit.	112,236.100	110,557.900	125,509.000	122,630.700

Note: All variable are defined in Section 3.2. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. Missing observations compared to table 3 are due to the lack of data of the original values of bilateral FDI flows for some year-country pairs, as well as the missing of the country-level variable for some year-country pairs.

In Table 7, columns (1) and (2) show the results under the immediate network, and columns (3) and (4) present the results under the historical network. We construct the investment connection variables using the purged FDI flows in columns (1) and (3), and apply the original values of FDI flows in the investment connection variables in columns (2) and (4). Note that all the results hold for the remaining geographic proximity and investment connection variables.

TABLE 6 Robustness check 2: Purged FDI stocks (probit regressions).

	Dependent variable: $y = 1[ODI_{f,c,t} > 0]$			
	Immediate network		**Historical network**	
	(1)	**(2)**	**(3)**	**(4)**
ODI Dummy at $t-1$	0.956***	0.908***	1.009***	0.937***
	(0.023)	(0.023)	(0.023)	(0.023)
Geo. Position	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Geo. Distance	0.036***	0.053***	0.047***	0.061***
	(0.002)	(0.002)	(0.001)	(0.002)
Geo. Network	0.006***	0.009***	0.002***	0.006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invest. Attraction	0.001***	0.0004***	0.0001***	0.0001***
	(0.00001)	(0.00001)	(0.00000)	(0.00000)
Invest. Intensity	0.005***	0.004***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.00002)	(0.00002)
Invest. Network	0.0001**	0.0003***	0.0001*	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP per capita		5.051***		5.814***
		(0.174)		(0.165)
ODI dummies from 0 to $t-2$	— No —		— Yes —	
Parameterized Firm FE with $y_0, Z_0, \overline{Z}$	— Yes —			
Year FE	— Yes —			
No. of Obs.	6,370,716	6,166,104	6,370,716	6,166,104
No. of Firms	— 3468 —			
No. of Countries	— 167 —			
No. of Years	— 11 —			
Pseudo R^2	0.141	0.154	0.118	0.138
Log Likelihood	−65,741.780	−63,773.890	−66,367.120	−63,821.910
Akaike Inf. Crit.	131,525.600	127,591.800	132,792.200	127,703.800

Note: All variables are defined in Section 3.2 and Appendix A. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. Missing observations in column (2) and (4) are due to the lack of data for the country-level variable for some year-country pairs.

TABLE 7 Robustness check 3: Country fixed effects (probit regressions).

	Dependent variable: $y = 1[ODI_{f,c,t} > 0]$			
	Immediate network		**Historical network**	
	(1) Purged	**(2) Original**	**(3) Purged**	**(4) Original**
ODI Dummy at $t-1$	0.698***	0.691***	0.693***	0.691***
	(0.023)	(0.023)	(0.023)	(0.023)
Geo. Network	0.009***	0.009***	0.007***	0.007***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Invest. Attraction	0.0004**	0.422***	0.0003***	0.003***
	(0.0002)	(0.158)	(0.00004)	(0.001)
Invest. Intensity	0.006***	0.006***	0.001***	0.001***
	(0.001)	(0.001)	(0.0002)	(0.0002)
Invest. Network	1.865***	1.911***	1.243*	0.002**
	(0.558)	(0.536)	(0.711)	(0.001)
GDP per capita	1.939	1.969*	2.279*	2.734**
	(1.185)	(1.188)	(1.217)	(1.224)
ODI dummies from t to $t-2$	— No —		— Yes —	
Parameterized Firm FE with $y_0, Z_0, \overline{Z}$	— Yes —			
Year FE	— Yes —			
Country FE	— Yes —			
No. of Obs.	6,166,104	5,593,884	6,166,104	5,593,884
No. of Firms	— 3468 —			
No. of Countries	— 167 —			
No. of Years	— 11 —			
Pseudo R^2	0.233	0.226	0.225	0.217
Log Likelihood	−57,859.950	−57,266.580	−57,447.720	−56,869.570
Akaike Inf. Crit.	116,081.900	114,865.200	115,271.400	114,085.100

Note: All variables are defined in Section 3.2. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. Missing observations compared to table 3 are due to the lack of data of the original values of bilateral FDI flows for some year-country pairs, as well as the missing of the country-level variables for some year-country pairs.

6 | CONCLUSION

We examine the impacts of geographical proximity and investment connection on how Chinese multinational firms expand globally by conducting outward FDI, including both greenfield investment and cross border merger and acquisition. We find two dominant geographical driving forces: a direct distance effect (geographic distance) and an indirect network effect (geographic network). A firm tends to invest in the country that is closer to China; and a firm makes use of its existing outward FDI network for further investment, radiating from the host country of their existing subsidiaries to the neighboring countries. Analogously, we also find two economic driving forces: a direct investment effect (investment intensity) and an indirect network effect (investment network). A firm is more likely to invest in a country with more intense Chinese outward FDI flows; and a firm takes advantage of its existing host countries' FDI network to make further investment decisions. These findings are robust when we use other geographic and investment measures, and put more control variables.

We develop a spatial model to simultaneously consider the impacts of both investment network structure and geographic network structure on the firm-level outward FDI destination choice. We find that the gravity property exists not only in the geographic proximity but also in the investment connection.

Moreover, the paper demonstrates a dynamic feature of the global expansion of a multinational firm. We find a firm's past outward FDI experience would affect its future outward FDI destination choice. Specifically, a Chinese firm tends to invest in a country that is both geographic closer and investment more connected to its existing outward FDI destination countries, which creates a hub—subhub—spokes network expansion path over the time. The long-term past active global expansion strategy of a multinational firm helps its future investment decision more than the macro-level bilateral FDI behaviors of China.

Last but not least, different from international trade, the historical network that takes into account all the past OFDI experience matters as well as the immediate network. Especially for the investment connection, the cumulative past OFDI experience plays a more important role than only the last period.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Ministry of Commerce of the People's Republic of China. Legal restrictions apply to the availability of these data.

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ENDNOTES

[1] We do not report the real name of the firm for data privacy. It is a private owned Chinese manufacturing firm specializing in sewing machine which was established a few years after China's reform and opening up policy in 1978 and has conducted multiple OFDI before and during in the data period.

[2] Mainland China and Hong Kong, China belong to"one country, two systems", so we generally consider investments from mainland multinational enterprises to Hong Kong, China as a kind of foreign direct investment.

[3] As initially proposed by Tinbergen (1962), the gravity model has been widely used in the international trade, including imports and exports, FDI, migration, intangible knowledge, and transportation (see more details in Anderson & van Wincoop, 2003; Lewer & Van den Berg, 2008; Keller & Yeaple, 2013; and Stone & Jeon, 1999).

[4] We use the intermediate-region standard from ISO-3166, which divide the world into 22 intermediate regions: North America, Caribbean, Central America and South America for America; Northern Europe,

Western Europe, Eastern Europe and Southern Europe for Europe; Northern Africa, Central Africa, Western Africa, Eastern Africa and Southern Africa for Africa; Western Asia, South-Central Asia, South-Eastern Asia and Eastern Asia for Asia; Australia, New Zealand, Melanesia, Micronesia and Polynesia for Oceania.

[5] The empirical specifications need a sequential OFDI investment activities for at least two periods.

[6] The number of observations of cross-border M&A is much smaller than that of greenfield investment because (1) Zephyr only documented closed deals of M&A; (2) we exclude all the tax heaven destinations including Cayman islands (CYM), Bermuda (BMU) and British Virgin Islands (VGB); (3) we also exclude all the personal deals since they cannot be identified with the companies they represented for.

[7] Given that the full history of OFDI data is usually not available, the model may suffer from the standard initial conditions problem. The fixed effect is introduced as a feasible solution to solve the initial conditions problem, but it gives rise to another concern, the incidental parameter problem, that is, the finite length time horizon cannot provide sufficient variation to estimate the individual fixed effect, suffering from the estimation bias. To address this estimation bias issue, several works have been proposed. Among them, Wooldridge (2005), further improved by Rabe-Hesketh and Skrondal (2013), proposed a simple solution by parameterizing the fixed effect into the estimation equation. It assumes that the fixed effect depends on the initial outcome value, and other observables in the data. In this way, it reduces the number of parameters in the estimation and also lets the initial conditions conditioning on other variables follow a separate distribution, which can be profiled out or separately estimated.

[8] Recall that we use the last period firm-specific effective distance between country c and China as $Z_{f,c,t-1}$, that is, $Z_{f,c,t-1} = g\left(d_{c,CN}\right) \times \mathbf{I}\left(ODI_{f,c,t-1} > 0\right)$ which contains $\mathbf{I}\left(ODI_{f,c,s} > 0\right)$, and therefore α_1 and δ cannot be separately identified.

[9] Specifically, Equation (4) is generated from

$$
\begin{aligned}
&\Pr\left(\mathbf{I}\left(\underline{ODI}_{f,t} > 0\right) | X_{c,t}, \dots, X_{c,1}, \underline{Z}_{f,t-1}, \underline{ODI}_{f,t-1}, \dots, \underline{ODI}_{f,1}, d_t\right) \\
&= F_{\sigma^2_{\xi_f}+1}\left(\alpha_1 \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \alpha_2 \mathbf{I}\left[\underline{ODI}_{f,t-2} > 0\right] + \dots + \alpha_{t-1} \mathbf{I}\left[\underline{ODI}_{f,1} > 0\right] + \beta_1 W_{g(d_{cc'})} \times \iota + \beta_2 \underline{g}\left(d_{CN}\right)\right. \\
&+ \beta_{3,1} W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \beta_{3,2} W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,t-2} > 0\right] + \dots + \beta_{3,t-1} W_{g(d_{cc'})} \times \mathbf{I}\left[\underline{ODI}_{f,1} > 0\right] \\
&+ \gamma_{1,1} W_{FDI_{cc',t-1}} \times \iota + \gamma_{1,2} W_{FDI_{cc',t-2}} \times \iota + \dots + \gamma_{1,t-1} W_{FDI_{cc',1}} \times \iota \\
&+ \gamma_{2,1} \underline{FDI}_{CN,t-1} + \gamma_{2,2} \underline{FDI}_{CN,t-2} + \dots + \gamma_{2,t-1} \underline{FDI}_{CN,1} \\
&+ \gamma_{3,1} W_{FDI_{cc',t-1}} \times \mathbf{I}\left[\underline{ODI}_{f,t-1} > 0\right] + \gamma_{3,2} W_{FDI_{cc',t-2}} \times \mathbf{I}\left[\underline{ODI}_{f,t-2} > 0\right] + \dots + \gamma_{3,t-1} W_{FDI_{cc',1}} \times \mathbf{I}\left[\underline{ODI}_{f,1} > 0\right] \\
&\left. + \eta \underline{GDPpc}_t + \delta \underline{Z}_{f,t-1} + (\kappa_0 + \kappa_1 y_{f,0} + \kappa_2 \overline{Z}_f + \kappa_3 Z_{f,0}) \times \iota + d_t \times \iota\right),
\end{aligned}
$$

with $\beta_{3,t-1} = \beta_{3,t-2} = \dots = \beta_{3,1} = \beta_3$, $\gamma_{1,t-1} = \gamma_{1,t-2} = \dots = \gamma_{1,1} = \gamma_1$, $\gamma_{2,t-1} = \gamma_{2,t-2} = \dots = \gamma_{2,1} = \gamma_2$, and $\gamma_{3,t-1} = \gamma_{3,t-2} = \dots = \gamma_{3,1} = \gamma_3$.

[10] The gravity model regressions of FDI flows and FDI stocks (robustness check) will be shown in the appendix (Appendix A).

[11] We use the purged FDI flows consistently in our main specifications as well as most of the robustness checks in the later sections, and we will run some robustness checks on the original values of bilateral FDI flows in Section 5.

[12] Alternatively, a more popular FDI destination country c may generate the competition effect for a Chinese multinational firm to invest in. We believe the positive network effect will be dominant.

[13] The summary statistics of the variables defined by the purged FDI stocks are reported in Appendix A.

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APPENDIX A

Purged FDI flows and purged FDI stocks

In order to construct the investment connection variables (investment attraction, investment intensity, and investment network), we need a set of clean bilateral FDI variables (FDI flows and FDI stocks) without the effects from the geographic distance we use to define the geographic proximity variables. And therefore we could separate the investment impacts from the geographic effects.

Like bilateral trade volume, both bilateral FDI flows and FDI stocks may follow the gravity property that are affected positively by the economy size (GDP) of the two countries and negatively by the geographic distance between them. We run the following gravity model regressions of bilateral FDI variables (flows and stocks) on the GDP of the two countries and the geographic distance.

$$\text{Bilateral } FDI_{i,j,t} = \alpha + \beta_1 lnGDP_{i,t} + \beta_2 lnGDP_{j,t} + \gamma lnGeo.Distance_{i,j} + \epsilon_{i,j,t}$$

where Bilateral $FDI_{i,j,t}$ are the FDI flows and FDI stocks from country i to country j in year t, $GDP_{i,t}$ is the GDP of the FDI origin country i in year t, $GDP_{j,t}$ is the GDP of the FDI target country j in year t, and $Geo.Distance_{i,j}$ is an inverse distance measure defined as 10,000 divided by the bilateral distance between country i and country j.

The summary statistics of the variables in the above gravity model are shown in Table A1. And the regression results are presented by Table A2.

Then we take the residuals from the two the gravity model estimations to generate purged FDI flow variable and purged FDI stock variable. The residuals eliminate all the potential effects

TABLE A1 Summary statistics of FDI gravity model.

Variables in FDI gravity model across 64,972 country-year pairs						
	Unit	**Max**	**Min**	**Median**	**Mean**	**SD**
FDI Flows	trillion $	109.097	−51.212	0	0.2086	2.2084
FDI Stocks	trillion $	645.098	−30.2371	0	2.1461	15.7519
Geo. Distance	10,000/km $	167.7367	0.5064	1.8407	4.2058	7.7938
Origin GDP	trillion $	16.1552	0.0001	0.2221	1.0078	2.3854
Target GDP	trillion $	16.1552	0.0001	0.1346	0.795	2.1824

TABLE A2 FDI gravity model estimations.

	Dependent variable	
	FDI flows	FDI stock
	(1)	(2)
Ln Geo. Distance	0.209***	2.062***
	(0.009)	(0.063)
Ln Origin GDP	0.111***	1.371***
	(0.004)	(0.028)
Ln Target GDP	0.114***	1.259***
	(0.004)	(0.028)
Constant	0.475***	5.567***
	(0.016)	(0.111)
Observations	64,972	64,972
R^2	0.026	0.065
Adjusted R^2	0.026	0.065
Residual Std. Error (df = 64,968)	2.180	15.233
F Statistic (df = 3; 64,968)	575.425***	1500.529***

Note: Standard errors are presented in parentheses.***, **, and * denote significance at 1%, 5%, and 10% respectively.

TABLE A3 Summary statistics of the purged FDI stocks.

Panel (a): Immediate network	Unit	Max	Min	Median	Mean	SD
Invest. Attraction (Purged Stock)	trillion $	1929	−199.2	−4.537	13.21	176.6
Invest. Intensity (Purged Stock)	trillion $	296.2	−12.42	0	−1.627	11.67
Invest. network (Purged Stock)	trillion $	1453	−199.0	0	3.491	34.33
Panel (b): Historical network						
Invest. Attraction (Purged Stock)	trillion $	15,795	−1659	−16.33	48.37	1060
Invest. Intensity (Purged Stock)	trillion $	1162	−119.7	−0.842	−8.308	43.01
Invest. network (Purged Stock)	trillion $	5544	−157.4	0	1.471	27.18

from the geographic distance as well as the economy size of the two countries. Applying the purged FDI flows and the purged FDI stocks, we construct two sets of the investment connection variables for both immediate network and historical network which are independent of the geographic proximity variables in the model specifications of the paper. The summary statistics of the investment connection variables using the purged FDI flows are reported in Table 2 of the paper. Table A3 reports the summary statistics of the investment connection variables using the purged FDI stocks.

APPENDIX B

Common region matrices and common language matrices

We define the geographic common region matrix and the geographic common language matrix as the following.

$$W_{g(d_{cc'}),R} = \begin{bmatrix} g\left(d_{1,1}\right)\cdot r_{1,1} & g\left(d_{1,2}\right)\cdot r_{1,2} & \cdots & g\left(d_{1,c'}\right)\cdot r_{1,c'} & \cdots & g\left(d_{1,C}\right)\cdot r_{1,C} \\ g\left(d_{2,1}\right)\cdot r_{2,1} & \ddots & & & & g\left(d_{2,C}\right)\cdot r_{2,C} \\ \vdots & & \ddots & & & \vdots \\ g\left(d_{c,1}\right)\cdot r_{c,1} & & & g\left(d_{c,c'}\right)\cdot r_{c,c'} & & g\left(d_{c,C}\right)\cdot r_{c,C} \\ \vdots & & & & \ddots & \vdots \\ g\left(d_{C,1}\right)\cdot r_{C,1} & g\left(d_{C,2}\right)\cdot r_{C,2} & & g\left(d_{C,c'}\right)\cdot r_{C,c'} & & g\left(d_{C,C}\right)\cdot r_{C,C} \end{bmatrix},$$

$$W_{g(d_{cc'}),L} = \begin{bmatrix} g\left(d_{1,1}\right)\cdot l_{1,1} & g\left(d_{1,2}\right)\cdot l_{1,2} & \cdots & g\left(d_{1,c'}\right)\cdot l_{1,c'} & \cdots & g\left(d_{1,C}\right)\cdot l_{1,C} \\ g\left(d_{2,1}\right)\cdot l_{2,1} & \ddots & & & & g\left(d_{2,C}\right)\cdot l_{2,C} \\ \vdots & & \ddots & & & \vdots \\ g\left(d_{c,1}\right)\cdot l_{c,1} & & & g\left(d_{c,c'}\right)\cdot l_{c,c'} & & g\left(d_{c,C}\right)\cdot l_{c,C} \\ \vdots & & & & \ddots & \vdots \\ g\left(d_{C,1}\right)\cdot l_{C,1} & g\left(d_{C,2}\right)\cdot l_{C,2} & & g\left(d_{C,c'}\right)\cdot l_{C,c'} & & g\left(d_{C,C}\right)\cdot l_{C,C} \end{bmatrix},$$

in which $r_{c,c'}$ equals one if country c and country c' locate in the same economic region, and zero otherwise; $l_{c,c'}$ equals one if country c and country c' share the same language, and zero otherwise; and the diagonal elements are zero. And therefore the inverse distance is taken into account if the two countries locate in the same economic region for the common region matrix and the two countries share the the same language for the common language matrix.

Similarly, we define the investment common region matrix and the investment common language matrix with $s = 1, 2, ..., t-1$ as the following to make the bilateral FDI flow only matters when the two countries locate in the same economic region for the common region matrix and the two countries share the the same language for the common language matrix.

$$W_{FDI_{cc',R,s}} = \begin{bmatrix} FDI_{1,1,s}\cdot r_{1,1} & \cdots & FDI_{1,c',s}\cdot r_{1,c'} & \cdots & FDI_{1,C,s}\cdot r_{1,C} \\ FDI_{2,1,s}\cdot r_{1,1} & & & & FDI_{2,C,s}\cdot r_{2,C} \\ \vdots & \ddots & & & \vdots \\ FDI_{c,1,s}\cdot r_{c,1} & & FDI_{c,c',s}\cdot r_{c,c'} & & FDI_{c,C,s}\cdot r_{c,C} \\ \vdots & & & \ddots & \vdots \\ FDI_{C,1,s}\cdot r_{C,1} & \cdots & FDI_{C,c',s}\cdot r_{C,c'} & & FDI_{C,C,s}\cdot r_{C,C} \end{bmatrix},$$

$$W_{FDI_{cc',L,t-1}} = \begin{bmatrix} FDI_{1,1,t-1} \cdot l_{1,1} & \cdots & FDI_{1,c',t-1} \cdot l_{1,c'} & \cdots & FDI_{1,C,t-1} \cdot l_{1,C} \\ FDI_{2,1,t-1} \cdot l_{1,1} & & & & FDI_{2,C,t-1} \cdot l_{2,C} \\ \vdots & \ddots & & & \vdots \\ FDI_{c,1,t-1} \cdot l_{c,1} & & FDI_{c,c',t-1} \cdot l_{c,c'} & & FDI_{c,C,t-1} \cdot l_{c,C} \\ \vdots & & & \ddots & \vdots \\ FDI_{C,1,t-1} \cdot l_{C,1} & \cdots & FDI_{C,c',t-1} \cdot l_{C,c'} & & FDI_{C,C,t-1} \cdot l_{C,C} \end{bmatrix},$$

in which the diagonal elements are zero.