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Gone with the epidemic? The spatial effects of the Covid-19 on global investment network

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ARTICLE INFO ABSTRACT Handling Editor: Dr. Y.D. Wei The outbreak of Covid-19 epidemic has a prolonged impact on global economic activities. In recent years, many scholars have been motivated to estimate the effects of Covid-19 shock on global foreign direct investment (FDI). Keywords: However, existing studies have not paid enough attention to the spillover effects caused by the epidemic. Covid-19 epidemic Although few academic works have explored the geographic-neighboring spillover effects of epidemic shock on Global investment network global investment, we further extent the understanding of the spillover effects in an economic network. On the Spillover effects basis of country-month greenfield FDI panels, we construct a spatial Durbin model, and figure out that Covid-19 Spatial analysis shock may have positive FDI spillover effects in an economic network via global FDI transfers. Furthermore, we find that such spillovers are greatly conditioned by country-level network position and institutional ties among nations. Our research suggests that global FDI transfers may partly offset economic-adverse effects of the Covid-19 shock. While global countries, especially those in the Global South, should be more closely embedded in the global investment network in such an uncertain environment.

"It was the best of times, it was the worst of times."

Charles Dickens

1. Introduction

The outbreak of Covid-19 epidemic remains an international hot topic until we write. The epidemic is not only a topic of gossip among residents, but also a black swan in the globalized economy(Ahmad et al., 2021). Since the New Year 2020, the number of people infected and the mortality rate skyrocketed, prompting countries to take strict restrictions on domestic production and international movement. Under such a circumstance, scholars have been motivated to identify the effects of Covid-19 epidemic on international economy and various sub-sectors (Dimian et al., 2021).

Recently, a group of reports have conducted detailed discussions on the substantial decline of FDI (foreign direct investment) flows during the ongoing public-health crisis. For example, the IMF (2020) report on the World Economic Outlook addressed that FDI registered in 2020 would face a 35% decline, with the worst result to return to the level of 2005 (UNTCAD, 2021). In general, the significance of FDI research in the context of Covid-19 epidemic is two-fold. On the one hand, FDI establishes an interaction between countries of origin and destination, however, such link may help epidemic contagion(Hysa et al., 2022). On the other hand, FDI plays an important role in both developed and developing countries. For example, in developed economies, FDI helps maintain sustainable market competitiveness(Jimborean & Kelber, 2017), export(Bhattacharya et al., 2012) and financial sources(Haque et al., 2022). While in developing countries, FDI enriches opportunities for employment growth(Inekwe, 2013), as well as capital and knowledge transfers(Guo et al., 2022).

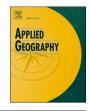
We focus on an important sub-sector of OFDI (outward foreign direct investment), that is, international greenfield investment projects (we use OFDI for convenience hereinafter). According to the definition, greenfield outward investment is conducted by multinationals that directly establish joint ventures and cooperative enterprises in the host country for production(Ashraf et al., 2016). It has higher requirements for the parent company's operating conditions and the host country's business environment than cross-border mergers and acquisitions. Thereby, the OFDI activities are always colored by national power (Demirbag et al., 2008). However, the outbreak of Covid-19 epidemic has fundamentally shifted national priorities and multinationals' profit-seeking strategies, greatly reshaping global OFDI landscape(Arif et al., 2021).

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In this paper, we start from the previous works on the negative impact of Covid-19 epidemic on FDI, and extend our discussion to the spatial spillover effects of the epidemic. Since previous studies mainly narrow down focus on the geographic spillover effects of the epidemic on global FDI(Florida & Mellander, 2022), we propose that the spillover effects of Covid-19 shock, both spatially and temporally(Zhang et al., 2022), can be inherently different in an economic network formed by global OFDI linkages. The above-mentioned spillover mechanisms are shown in Fig. 1 below. The left panel of Fig. 1 shows a schematic diagram of typical geographic spillovers of the epidemic. It is straightforward that the geographical spread of epidemics causes national OFDI to be affected by outbreaks in neighboring countries(Krisztin et al., 2020). However, the story may be different in an economic space (network). On the right-hand side of Fig. 1, if country D witnesses an epidemic shock (the victim, hereinafter), the OFDI inflows from the rest of world (hereinafter, RoW) to D would be forced to decline, due to local-market protection policies or lower production capabilities (higher risk and higher costs). In this case, we may observe OFDI reshoring or relocating (Haberly & Wójcik, 2015). Then, if the OFDI demand transfers to country E,¹ the destination would witness increasing OFDI inflows, that is, positive spillovers of epidemic shock in the global OFDI network.

What we are curious about is the relationship between those "*country* D'' and "*country* E". The marginal contribution of our research is as follows. We synthesize three branches of literature in our theoretical analysis, that is, international business literature on the impact of Covid-19 epidemic, economic geography literature on FDI location choice and social network analysis literature on network formation, respectively. With the help of spatial econometric and network analysis methods, we figure out that countries have an OFDI linkage to the victim may witness positive spillovers in the context of Covid-19 shock. Moreover, the network-position and institutional guarantee of the victim-partner condition such effects. Countries at the periphery of the network, and those with signed BITs (bilateral investment treaties) with the victim, are more receptive to OFDI transfers from the RoW.

The remaining part of this paper is as follows. Section 2 presents our theoretical framework in an interdisciplinary context and elaborates logical clues behind our research hypotheses. Next, section 3 and section 4 respectively display measurement and spatial econometric strategies. Then, section 5 includes a necessary condition analysis based on an ERGM model to consolidate our findings. Finally, section 6 opens a discussion and concludes our research.

2. Literature review

2.1. Covid-19 as a shock to global OFDI

The general view is that the outbreak and lasting of Covid-19 epidemic has seriously hindered international economic activities, such as bilateral trade(Liu et al., 2022), foreign direct investment and transnational transactions(Vidya & Prabheesh, 2020). Also, it has been widely recognized that the global public health shock negatively impacts global economy via weakening domestic and foreign consumption and investment demand, inhibiting the input of production factors and reducing opportunities for face-to-face communication(Brodeur et al., 2021).

Recent articles have addressed the negative impacts of Covid-19 shock, illustrating how containment policies, supply chain disruptions and diving fall in the demand have impeded international offshoring activities(Wiesmann et al., 2017). According to its definition, international offshoring (in international business) is the performance of an international activity in a country different to from where a firm's

headquarters are located(Grossman & Rossi-Hansberg, 2008). In international offshoring activities, OFDI is one of the most typical representatives of overseas production. OFDI not only reflects the profit-making behavior of enterprises' investment, but also represents the role of national power in oversea economic activities(Haberly & Wójcik, 2015). Due to the shock led by Covid-19 epidemic, on the one hand, enterprises, especially small and medium enterprises, are facing with the increasingly decline of profit expectations and willingness to invest(Bartik et al., 2020), which affects overseas investment decisions at the enterprise level(Fairlie, 2020). On the other hand, de-globalization and reshoring tends to be mounted among policy makers and scholars. Multiple countries have issued even more stringent FDI screening policies to protect national interests. Correspondingly, under the will of the country, overseas factories and plants are facing closure, reshoring or relocating(Di Stefano et al., 2022).

The above-mentioned impacts of the Covid-19 epidemic on international economic activities is only the tip of an iceberg. In other words, the shock does not only affect a certain country, but has a contagious effect like a virus. Some cutting-edge research has paid attention to the geographical spillover effects of the Covid-19 epidemic on OFDI. Intuitively speaking, the spread of the epidemic is much more likely to occur between countries that are spatially adjacent to each other(Florida & Mellander, 2022). Therefore, the outbreak of an epidemic in a country may not only affect its own overseas economic activities, but also hinder the economic activities of its neighbors(Hasan et al., 2021). Furthermore, geographic distance, measured by spherical distance or international flights frequency between countries, potentially conditions such negative spillover effects(Coven et al., 2023).

2.2. Beyond the geographical spillover effects of Covid-19 on OFDI

However, existing literature still pays less attention on the nongeographic spillover effects of the epidemic on economic activities. We introduce a network perspective, on the basis of geographic spillover effects, to examine the impact of the epidemic on OFDI. Bilateral direct investments contribute to the formation of global OFDI network. Once a node in the network is affected by the epidemic, its adjacent nodes need to reconsider investment decisions. Hence, what we are interested in is the impact of the epidemic on nodes adjacent to the country-of-victim.

Previous literature has summarized the location selection rules of the country and foreign firms in oversea investment decision-making(He, 2002). For example, TCE(transaction cost economics) and RBV (resource-based view) rules aim at explaining the decision of firms to move from high-cost to low-cost environment and exploit competitive advantages(Wernerfelt, 1984). While the OLI model shows that firms participate in international activities if internalization advantages are present(Dunning, 2009). Start from these theories, some articles have focused on the Covid-19-led OFDI shift, addressing the important issues such as OFDI reshoring or relocating(Di Stefano et al., 2022). To account for the spillover effects of Covid-19 shock on the global OFDI network, we further look into OFDI relocating led by the epidemic. Given the total OFDI demand in the global economy, if the victimized country sets up FDI barriers, OFDI from the RoW would be more likely to transfer to other destinations. On the one hand, it is an important force in the current global competition to reshore the production manufacturers to the domestic market or transfer them to other overseas markets(Reddy et al., 2022). On the other hand, countries may directly shift their future investment decisions if they witness potential barriers in targeted markets(Lee et al., 2020). In this sense, the epidemic may have a negative impact on a single country's OFDI input and output, but from a network perspective, we may observe positive spillovers especially on countries' OFDI input(Bettarelli & Resmini, 2022). Therefore, we should expect the following.

H1. Covid-19 shock may have negative spillover effects on OFDI in a geographical-adjacency network, but it may have the opposite outcome

¹ The OFDI transfers here can be two-ways according to the theory of binary margins, that is, the RoW may create new OFDI link between itself and country E or simply strengthen existing linkages.

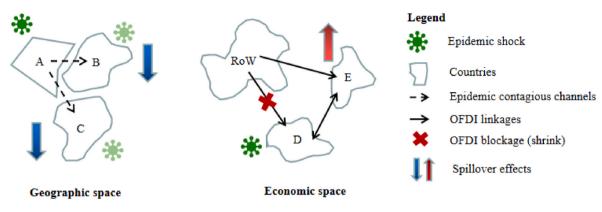


Fig. 1. The spillover effects of Covid-19 epidemic on OFDI.

Note: Countries A to C are geographically adjacency countries. Geographical adjacency can be measured by common borders, distance, international flights, etc. Country D and country E are not necessarily proximate in terms of geographic distance. The economic space is more like a relational network, and international OFDIs bind all countries together in our case.

in an economic network represented by international OFDI linkages.

2.3. The directions of Covid-19-led spillover effects on OFDI network

So far, we have proposed that the global epidemic may facilitate OFDI transfers, thereby generating positive spillovers on the OFDI network. However, we still need to analyze what specific spillover paths are, that is, which countries are more likely to receive OFDI transfers from the RoW. To answer the question, we attempt to combine the economic geography literature on FDI location research with the social network analysis (SNA) literature. As mentioned above, FDI location selection researches have provided extensive information on decision-making and destination choice of FDI offshoring, reshoring and relocating(Blanc-Brude et al., 2014). However, from a network perspective, such findings only work on network nodes, but do not combine the classic FDI location research literature with the social network research literature(Bettarelli & Resmini, 2022).

Inspired by the SNA literature, we take a further step on discussing the directions of positive OFDI spillovers brought by the epidemic. In terms of the overall properties of a network, the SNA scholars believe that structural holes possess information superiority(Burt, 1992). A structural hole, according to its definition, is an individual node who bridges the gap between different clusters(Burt, 2004). With such a position, a structural-hole-type node is able to absorb information from its neighbors(Burt et al., 1998), and continuously consolidate its position superiority through "preferential attachment" (Barabasi & Albert, 1999). If this mechanism holds, in our OFDI network, a structural-hold-type country may absorb much more transferred OFDI from the RoW if some of its neighbors become Covid-19 victims. However, some recent studies have pointed out that structural holes in the network may also have negative effects. For instance, Bizzi (2013) argues that the node occupying the structural hole position always has greater self-adjustment power than its peers. In this way, it is easier for the structural-hole-type node to establish information barriers and change the direction of flows in the network(Sparrowe et al., 2001). In terms of nodes in the OFDI network, those countries with larger OFDI input and output (node degrees), such as USA, China and Japan, usually occupy the core position. Interestingly, under the background of the epidemic, these network-dominant countries may witness a decline in OFDI flows. Such "decline" can be possibly attributed as follows. First, countries with core positions in the OFDI network are always important global investors, so that instinctually they could have larger numbers of overseas projects. Therefore, the outbreak of the epidemic might lead to statistical significant OFDI decline. Second, from the perspective of national capability(Chasedunn, 1975), these "core" countries may have more opportunities to exploit domestic market, hedging the uncertainty

in the international market. In this way, they may actively seek for OFDI-substitution policies(Goh & Wong, 2014). On the contrary, we believe that countries at the periphery of the OFDI network are more dependent on worldwide investments. Hence, these countries may become key destinations for transferred OFDI from the RoW. Accordingly, we should expect the following.

H2. Countries at the periphery of the global OFDI network may have chance to receive much more transferred OFDI from the RoW. Statistically, these countries may witness more positive spillover effects.

The last remaining question is about the edge relationship in the OFDI network. We are curious to find out whether countries with OFDI ties to the Covid-19 victims receive more spillovers from the RoW. According to the gravity model commonly used in FDI location selection studies, national attributes, such as distance(Blanc-Brude et al., 2014), economic aggregate(Liu et al., 2016), population(Mitra & Abedin, 2022), market size(Wei & Liefner, 2012), culture(Fiorini et al., 2021) and institutional environment (Huang & Wei, 2016), are important factors for attracting foreign investment. The basic intuition behind the gravity model is that when a firm chooses an investment destination, it tends to choose a country that is similar to its home country. In other words, multidimensional proximity matters a lot in destination choices (McDonald et al., 2018).Start from the proximity in international business and economic geography literature, a SNA perspective further focuses on the role of node assortativity in network formation. Assortativity is a preference for a network's nodes to attach to others that are similar in some way(Newman, 2003). The "in some way" here is usually represented by feature vectors of nodes, that is, their attributes (Noldus & Van Mieghem, 2015). Thus, the proximity of countries' attributes (e.g. market potential, language, institution) can be abstracted into node assortativity, which leads to the formation of edges (OFDI flows) among network's nodes(Li et al., 2018). Specifically, we can speculate that under the impact of the epidemic, countries connected to the Covid-19 victims (with OFDI linkages with corresponding nodes) may witness more greenfield investment transferred from the RoW than those isolated counterparts. Again, if the victims lose production capacity or set up stricter FDI barriers, its neighbors with assortative attributes in the OFDI network can be ideal receivers for transferred OFDI from the RoW. To conclude, both the priori OFDI network formation channel and the posteriori OFDI destination selection channel shed light on the importance of country-level attributes. Thereby, we should refine the first two hypotheses and expect the following.

H3. Countries connected to the Covid-19 victims may witness more positive spillover effects. Potential channels behind is node assortativity, represented by proximity matrices such as geographic distance, cultural similarities and institutional setting.

3. Data and measurement

3.1. OFDI flows

We use the fDi Markets database to aggregate country-monthly OFDI data. Collected by the Financial Times, the fDi Markets data mainly from government directories, corporate annual reports, media resources, and email companies. Overall, the database tracks about 80% of global FDI data records, covering information on greenfield investment projects in all countries around the world. Compared with traditional foreign investment data sets, the fDi Markets records the real overseas investment project information rather than investment approvals. Therefore, we believe that our OFDI data is more realistic, since approved projects may not necessarily be fully put into production.

Taking into account the timing of Covid-19 outbreak and the recording of epidemic data in different countries, we test the abovedescribed hypotheses using a spatial panel of more than 150 countries from January 2017 to December 2021(with n > 9000). It is noteworthy that we follow Doytch et al. (2021) and regard the number of greenfield investment projects instead of the total investment amount as the main dependent variable. On the one hand, the fDi Markets only provides estimated amount of each investment project. On the other hand, the investment amount of different projects in the world varies greatly, thus using total investment amount is misleading for analyzing the strength of investment linkages between countries. For example, in 2015, Beijing Automotive Industry invested \$17million to Aachen, Germany. However, two years later, Huajian Group (a Chinese shoe-making company) invested \$1.5billion to Aba, Nigeria. Although the investment amount to Germany is one-tenth of that to Nigeria, China has stronger tie with Germany in the OFDI network according to the number of investment projects.

3.2. OFDI networks

Using the above-mentioned data, we construct a transnational OFDI network G = (V, E). In this network, V represents a vector of nations (districts), and E represents corresponding OFDI flows between any two nations (districts). To illustrate potential OFDI transfers caused by Covid-19 epidemic, we present real-world OFDI dynamic networks from 2019 to 2021 (Fig. 2). The maximum spanning tree (MST) of the OFDI matrix is calculated to make sure that the set of links connecting all the nodes in the network using maximum possible sum of OFDI flows and minimum number of connections. We use Kruskal's algorithm in Cytoscape software to calculate the MST. Next, we follow Hausmann and Hidalgo (2013) and add the strongest 10% connections that are not selected for the MST. In doing so, the visualization of our multi-layer OFDI networks can be shaped well (usually a network can be better visualized if the number of edges is 5 times as large as its number of nodes vertices). In addition, the total number of OFDI projects among countries in the corresponding time period is employed to indicate connection strength.

In Fig. 2(a), blue lines represent OFDI exit while orange lines represent OFDI entry between countries. The connection is counted as exit if the OFDI flow does exist at 2019 but disappears at 2021. Similarly, the connection is regarded as entry if the OFDI flow does not exist at 2019 but exists at 2021. It is obvious that after the outbreak of Covid-19 epidemic, in 2021, greenfield direct investment flows among many country-pairs disappeared. Especially at the core area of the network, OFDI inflows and outflows shrunk significantly in countries like the United States, the United Kingdom, France, China. As for the birth of new OFDI linkages, it can be observed that most orange lines appear between periphery and semi-periphery countries in the network. In Fig. 2(b), we map the increasing trend of the number of OFDI projects between countries. The key literature emphasizes the binary margin of international investment flows, that is, creating new linkages or strengthening existing linkages (Zhao et al., 2020). Here, thicker gray

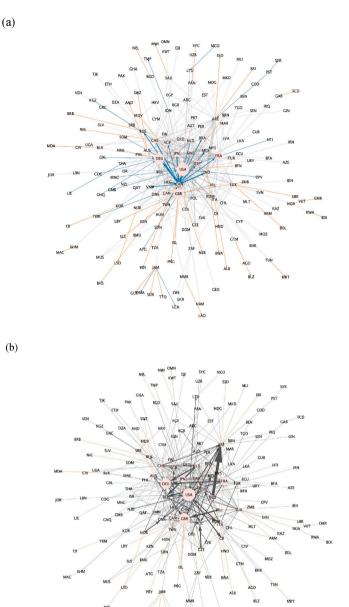


Fig. 2. The dynamics of flows in OFDI networks from 2019 to 2021. Note: blue lines = OFDI exit, orange lines = OFDI entry, gray lines = OFDI coexistence, circle size = total outflows.

line indicates a strengthened existing OFDI linkages between countries. An interesting phenomenon is that although some key nodes were suffering investment decline in 2021, the existing connections between nodes in the core area of the network increased significantly.

We can learn from the description of Fig. 2 that, first, the global epidemic has not destroyed the global OFDI network. Although some countries have reduced the amount of OFDI invested or received, OFDI transfers may have compensated for the adverse effects of the epidemic. For example, Germany's investment ties with China have weakened, but its ties with regional partners such as the Netherlands and France have strengthened. To be specific, OFDI transfers may manifest as entry into new markets or strengthening ties with existing partners. Hence, OFDI relocating rather than reshoring may enhance the positive spillover effects of the epidemic shock on the global OFDI network. Second, we observe that countries with smaller network degree have witnessed more strengthened ties with their partners. Take the United Arab

Emirates (UAE) as an example, its relationship with investment partners in Asia, America, and Europe showed a significant trend of strengthening. This fact echos our hypothesis that countries located at the periphery or semi-periphery of the network may witness more positive spillovers from the RoW if his partners become Covid-19 victims.

3.3. Covid-19 shock

Existing literature uses multiple methods to measure Covid-19 shock. One of the most popular ways is to regard confirmed rate, recovery rate and death rate as key proxies for the epidemic shock(Ascani et al., 2021). Besides, some socioeconomic researches implement dummy variables, such as stringency index and vaccination index, to address the dark side of the epidemic(Ang & Dong, 2022).

Inspired by these measurements, we construct a dummy variable to proxy Covid-19-led shocks in each country. First, we summarize the number of new confirmed cases of Covid-19 in worldwide countries (districts). Second, we calculate the confirmed rate based on the total population of the country. Third, to construct the dummy variable, we identify the outbreak periods for each country as if the confirmed rate of the country in a certain month is higher than the median rate of the full sample. Although the method is naive and fundamental, it has advantages in two-fold. First, we can approach monthly epidemic diagnosis data easily via the open access database of Johns Hopkins University. While the country-level population data is downloaded from the World Bank. Second, since many countries have relaxed epidemic control after 2021, using continuous variables, such as confirmed cases and death cases, may lead to larger errors. In general, our dummy variable is able to account for the instantaneous impact of the control policy after the outbreak of the epidemic. Meanwhile, it also reflects heterogeneous performance of different countries in the epidemic.

However, the usage of shock dummies may have caveats. On the one hand, the calculation is heavily based on the total infection in a certain country. Although some countries (e.g. China) had a relatively low-level confirmed rate at the beginning of 2020, its epidemic prevention policies had huge impacts on personal behaviors and economic organization (Zhang et al., 2020). On the other hand, our shock dummies are not sensitive to the time of period due to median comparison. To address these potential problems, we will later replace the current independent variable with a stringency index (from the Oxford Coronavirus Government Response Tracker, OxCGRT) to check robustness.

3.4. Country attributes

We collect a series of country-specific variables from the World Bank database. To address the channel proposed in hypothesis H3, we focus on proximity indicators between countries. The geographic proximity between two countries is measured in spherical distance. Also, we proxy culture proximity by identifying the co-occurrence of languages, laws and religions in a certain country pair. Thus we consider two countries to be culturally close if they share a common official language, legal system, or religion. All of these measurements can be downloaded from CEPII Gravity Database. Finally, we address the importance of national power in OFDI network formation. Here, we use institutional proximity to depict similar national wills in foreign investment. However, international-level institutional proximity is hard to be measured. Hence, we turn to information about bilateral investment treaties (BITs) provided by UNCTAD Investment Policy Hub. BITs are agreements establishing the terms and conditions for international investments by nationals and companies of one state in another state. Scholars have shown that BITs play a safeguard role in FDI activities(Falvey & Foster-Mcgregor, 2018), which also form an institutional norm among contracting states with a similar legal attitude towards foreign investment(Colen et al., 2016). We get the BITs raw data from UNCTAD's hub, restricting the date of signature to our study period. We keep treaties with the status of "in force" or "signed", and integrate them into an

institutional-proximity network.

4. Analytical strategy

4.1. Model setting

A spatial econometric model is a classic means to describe the spillover effects (of Covid-19 shock) on geographical space and OFDI network space(Elhorst, 2010). In this study, we construct a typical spatial Durbin model (SDM) to estimate the spillover effects of Covid-19 shock. Our SDM can be expressed as following:

$$OFDI_{ct} = \gamma_0 + \gamma_1 W \cdot OFDI_{ct} + \gamma_2 W \cdot shock_{ct} + \gamma_3 shock_{ct} + \mu_c + \nu_t + \varepsilon_{ct}, \quad (E1)$$

In equation (E1), the dependent variable $OFDI_{ct}$ is the number of foreign greenfield investment projects summarized by country *c* and month *t*, which can be further divided into the number of greenfield investment projects received (inflow) and the number of greenfield investment projects invested (outflow). *W* is spatial weight matrices, which depict the spatial relationship of sampled countries. *Shock_{ct}* represents our dummies that capture Covid-19 shock in country *c* and month *t*. Finally, $\mu_c v_t$ and ε_{ct} represent country fixed effects, month fixed effects and error terms, respectively. Furthermore, a SDM model shown in equation (E1) can be extended to a dynamic spatial Durbin model (DSDM) if lagged terms of the explained variables are added. The DSDM is shown in equation (E2) as:

 $OFDI_{ct} = \lambda_0 + \lambda_1 OFDI_{ct-1} + \lambda_2 W \cdot OFDI_{ct-1} + \lambda_3 W \cdot OFDI_{ct} + \lambda_4 W \cdot shock_{ct} + \lambda_5 shock_{ct} + \mu_c + \nu_t + \varepsilon_{ct}$ (E2)

4.2. Pre-processing of the dependent variable

One major concern in our model is that the dependent variable can be timely autocorrelated, that is, the number of OFDI projects in a country may be affected by the periodicity or trend of the time series. In terms of periodicity, macroeconomic fluctuations are inherently cyclical, which may have an unobserved impact on international investment(Dabla-Norris et al., 2015). On the other hand, OFDI and business cycle shows synchronization(Jos Jansen & Stokman, 2014), which further troubles our estimation. In terms of economic trend, the number of OFDI projects can be greatly influenced by other unobserved factors as well. For example, we cannot deny the fact that the China-United States trade friction and the Russo-Ukrainian War have greatly reshaped international OFDI structure. Therefore, such long-lasting events may lead to miscalculation on the economic impact of the epidemic.

We implement an ARCH (autoregressive conditional heteroskedasticity) model with a MA (moving average) to segregate periodicity and trend terms from our OFDI series. The ARCH model is commonly employed in modeling financial time series that exhibit timevaring volatility(Harvey et al., 1992). Since our OFDI projects series fluctuate greatly, we believe there might be variance autocorrelation in inter-temporal investment decision-making. The expression of our ARCH model is specified in Appendix A, and we obtain the residual terms from raw series. The residual terms, which is more informative on the epidemic shock, will be plugged into our SDM equation for coefficients estimation.

4.3. Spatial weight matrix

In our baseline regressions, we respectively take distance matrix, adjacency matrix and economic (OFDI) matrix as a spatial weight matrix (*W*) and estimate the spatial coefficients. The signs and values of γ_2 in equation (E1) shows different types of spillover effects of Covid-19 shock on OFDI in geographic and economic networks. In addition, we construct a degree-distribution matrix to capture the position of each country in the network. We also use multiple proximity indicators to

construct cultural proximity and institutional proximity matrices. The detailed description of spatial weight matrices we used are recorded in Appendix B.

The identification of moderating effects in econometric models is usually achieved by estimating the interaction terms between independent variables, but a typical spatial panel model does not provide solutions for the moderating effect between networks. What we are interested in is the moderating effects between networks, for instance, whether BIT relationship between a Covid-19 victim and his partners leads to more positive OFDI spillovers from the RoW to the victim's institutional-proximate partners. To detect the moderating effects of node degree and proximity on the Covid-19 spillovers along the OFDI network, inspired by previous works on spatial weight matrix integration(Case et al., 1993) and high order spatial models(Lee & Liu, 2010), we perform a Hadamard production for spatial weight matrices. In mathematics, for two matrices *A* and *B* of the same dimension $n \times n$, the Hadamard production $A \odot B$ is a matrix of the same dimension with elements given by:

$$(A \odot B)_{ij} = (A)_{ij} (B)_{ij}$$
(E3)

An example of equation (E3) is recorded in Appendix B as well. For instance, if the value of each element (0 or 1) in matrix A represents OFDI linkages between two countries, while that (0 or 1) in matrix B represents BIT linkages of the corresponding country-pair. Then, in terms of economic intuition, the value of each element in matrix $A \odot B$ (in this case also 0 or 1) captures whether investment and institutional linkages co-occur between the countries.

5. Results

5.1. Baseline regressions: a SDM estimation

We start from estimating the parameters in equation (E1). To identify the direction of spillover effects and the shock of Covid-19 on OFDI activities, we are especially interested in the signs of γ_2 and γ_3 in the equation. The spatial regression results are recorded in Table 1 below.

Each column of Table 1 records the coefficients under the estimation of the corresponding spatial weight matrix. Overall, we observe that estimated parameters of $shock_{ct}$ have negative signs, which shows that Covid-19 shock has a negative impact on global OFDI. Our findings echo the previous literature that the outbreak and lasting of Covid-19 epidemic has seriously hindered international economic activities(J. Abel G & Gietel-Basten, 2020). Next, we focus on the spillover effects of Covid-19 shock. Our regression results provide evidence that Covid-19 shock leads to heterogeneous spillover effects in different spaces. Column (1) to column (4) record negative signs of W^*shock in geographic networks. The results highlight that the outbreak of epidemic in a country may negatively affect OFDI in its geographically-close countries.

Such results do not hold when we shift to an economic matrix estimation. The positive sign of spillover effects illustrates that countries have OFDI linkage (receivers or investors) with the Covid-19 victims tend to witness more OFDI inflows. However, interestingly, the statistical results in column (5) show that the partners of the victims may not increase their OFDI outflows.² The explanation for this phenomenon is straightforward that the partner-countries of the victims have the role of substitutes to undertake the transfer of investment demand from the RoW. Also, when we further decompose the total effect of the epidemic shock, we figure out that the indirect effects in the OFDI network partly offsets the negative shock of Covid-19 on national OFDI inflows. In Applied Geography 156 (2023) 102978

Appendix C, we use a DSDM and re-estimate the coefficients of interest. Corresponding results recorded in Table A1 further support that our hypothesis H1 partly holds in OFDI-inflow, that is, greenfield investment transfers around the world may counterbalance the negative impacts of the epidemic on national economic activities. Besides, we find that the positive spillover effects of Covid-19 shock are even prominent in the long-run. Such evidence indicates that the epidemic shock could have lagged impact on global investment transfers, since countries (and multinationals) take time to adjust expectations as well as follow-up investment strategies.

To further check the robustness of our estimations, we add additional sensitivity analyses as follows. First, we replace the key independent variable with the stringency index (as we mentioned in section 3.3). In detail, the OxCGRT project calculate the monthly-basis index, which includes a composite measure of nine metrics such as school closures and event cancellation. We regard the average stringency index provided by the database as a posterior measurement of the epidemic shock. Besides, we further generate the interaction term between our original shock dummy and the stringency index, to better capture the scope of the extreme crisis. Re-estimated results are recorded in the Append D Table A2 and Table A3, respectively. Second, we relax the two-way fixed effects and include a series of control variables to our regressions. Our control variables capture the country attributes, such as national FDI dependence, GDP, population and land area. In addition, we control the monthly bilateral trade value and monthly level of economic conflicts between China and the US. In this way, the effects of US-China trade war could be further eliminated. Corresponding robustness-check results are listed in Table A4. In general, our estimations are robust.

5.2. Heterogeneity: node's position in the OFDI network

We have argued that the structural-hole advantages in SNA may not hold in our OFDI case. To identify the network-position heterogeneous effects, we divide all countries into three groups, namely core countries, semi-periphery countries and periphery countries, according to total OFDI flows (node degrees). The grouping regression results are recorded in Table 2 below.

In Table 2, it can be seen from the regression coefficients of *W*shock* that only semi-periphery and periphery countries witness positive spillovers from Covid-19 shock on their OFDI partners. We further decompose the indirect effects into short-run and long-run effects, and figure out that the coefficients of long-run indirect effects are larger than those of short-run indirect effects. In a spatial econometric estimation, the LR effects take both spatial and temporal lagged influences of the independent variable into consideration. Here, in Table 2, we observe larger coefficients for the LR effects, which can be interpreted as that the intense of spillovers would augment with the proceeding of the time of period. The corresponding economic intuition is that the outbreak of the epidemic could lead to a relative long-term shock on international economic activities. The findings partly support hypothesis H2 that countries at the periphery of the global OFDI network may have chance to receive much more transferred OFDI from the RoW. In contrast, core countries in the network may have stronger self-adjust capability under the shock of Covid-19, that is, they are able to switch to domestic production and reduce OFDI flows with overseas countries. In this way, as victim's partner, a core country may still block OFDI transfers from the RoW to protect its own market. Thus, statistically speaking, a core country still witnesses negative spillover effects. Considering the extreme prominent roles of China and the US in the OFDI network, in the robustness check, we exclude them from the country sample and implement regressions based on different independent variables (Table A5). The clustering results mentioned-above are still hold.

es as depen- 5.3. Mechanisms: multi-proximity and OFDI transfers

 $^2\,$ In following regression analysis we only take OFDI inflow series as dependent variables, since the spillover effects in OFDI outflows are neither significant nor robust.

The above results have underpinned the fact that the OFDI partners,

Table 1

The spillover effects of Covid-19 shock on OFDI: a two-way fixed-effect SDM analysis.

Matrix (W)	Distance		Adjacency		Economic	
	(1) OFDI_in	(2) OFDI_out	(3) OFDI_in	(4)	(5) OFDI_in	(6)
				OFDI_out		OFDI_out
shock	-0.495*	-0.057	-0.629**	-1.150***	-1.024***	-0.409*
	(-1.70)	(-0.24)	(-2.16)	(-4.92)	(-3.83)	(-1.95)
W*shock	-0.946**	-1.385^{***}	-1.935***	-0.505*	0.580**	-0.270
	(-2.41)	(-4.10)	(-5.71)	(-1.79)	(2.01)	(-1.24)
W*OFDI	0.668***	0.647***	0.121***	0.133***	0.100***	0.119***
	(23.27)	(23.05)	(13.63)	(14.68)	(18.64)	(20.01)
Direct effects	-0.518*	-0.081	-0.685**	-1.162^{***}	-1.013^{***}	-0.402*
	(-1.75)	(-0.34)	(-2.36)	(-4.96)	(-3.70)	(-1.87)
Indirect effects	-3.899***	-4.066***	-1.847***	-0.603***	0.514*	-0.374
	(-5.04)	(-6.32)	(-6.46)	(-2.58)	(1.72)	(-1.64)
Total effects	-4.417***	-4.147***	-2.533***	-1.764***	-0.499**	-0.777***
	(-6.13)	(-7.02)	(-11.64)	(-9.62)	(-2.06)	(-3.98)
country FE	Yes	Yes	Yes	Yes	Yes	Yes
time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9120	10,020	9120	10,020	9600	10,680
R-squared	0.024	0.026	0.017	0.012	0.004	0.018
N	152	167	152	167	160	178

Note: Z-statistics in parentheses. OFDI series are measured by residual terms. All the spatial matrices are row-standardized. ***p < 0.01, **p < 0.05, *p < 0.1.

 Table 2

 Network-position grouping regression results.

Matrix (W)	Economic matrix OFDI_in					
Variable	(1)	(2)	(3)			
	core	semi-periphery	periphery			
W*OFDI	0.111***	0.132***	0.118***			
	(11.28)	(10.14)	(10.43)			
L.OFDI	0.432***	0.447***	0.446***			
	(44.71)	(46.39)	(46.43)			
L.W*OFDI	-0.039***	0.057***	0.049***			
	(-4.06)	(4.54)	(4.40)			
shock	-0.181	-0.543**	-0.165			
	(-0.77)	(-2.35)	(-0.71)			
W*shock	-2.161***	0.993**	1.067**			
	(-4.85)	(2.29)	(2.42)			
SR_Direct	0.203	-0.518**	-0.141			
	(0.91)	(-2.34)	(-0.63)			
SR_Indirect	-0.795***	0.340**	0.363**			
	(-5.24)	(2.50)	(2.53)			
SR_Total	-0.592**	-0.178	0.222			
	(-2.34)	(-0.73)	(0.78)			
LR_Direct	0.357	-0.937**	-0.255			
	(0.91)	(-2.34)	(-0.63)			
LR_Indirect	-1.418***	0.616**	0.656**			
	(-5.30)	(2.52)	(2.53)			
LR_Total	-1.062**	-0.321	0.401			
	(-2.37)	(-0.73)	(0.78)			
country FE	Yes	Yes	Yes			
time FE	Yes	Yes	Yes			
Observations	9440	9440	9440			
R-squared	0.195	0.186	0.183			
N	160	160	160			

Note: Z-statistics in parentheses. OFDI_in series are measured by residual terms. Using row-standardized economic matrix for estimation. SR = short-run, LR = long-run. ***p < 0.01, **p < 0.05, *p < 0.1.

especially those semi-periphery and periphery partner-countries of Covid-19 shock victims, may receive much more OFDI transfers from the RoW. Inspired by economic geography literature on FDI location choice and SNA literature on node assortativity, we further check the potential mechanisms behind such as geographic distance, cultural similarities and institutional setting.

In Table 3 column (1), we use the Hadamard production of geographic-adjacency matrix and OFDI matrix to re-estimate coefficients of interest. The coefficients of *W*shock* is significantly negative at 5%-level, that is, OFDI transfers from the RoW may not necessarily flow to geographic-close countries of the Covid-19 shock victims. In other words, in global economy, OFDI destination-shift is not a regionalrestricted behavior under the shock of Covid-19 epidemic. The explanation for this argument is that the geographies of colliding epidemics dominant the negative spillover effects(King & Rishworth, 2022). For example, neighboring countries in Southeast Asia, such as Thailand, Cambodia and Myanmar, have a high similarity in Covid-19 outbreak cycle. Thereby, the regional-outbreak of epidemic could significantly reduce international OFDI inflows.

Next, we shift to the cultural and institutional proximity between countries. The results recorded in column (2) and column (3) show that national power (measured by BIT relationship) outweighs cultural similarity, at least under the impact of Covid-19 epidemic, in promoting OFDI transfers. We only observe significant positive coefficient of W*shock under the estimation of institution \odot economic matrix, supporting the fact that an additional BIT linkage leads to more OFDI transfers from the RoW to the partners of the victim-country. Besides, the positive spillover effects tend to be even prominent in the long-run. Different from related studies that consider cultural proximity as an important bridge in OFDI network formation(Karreman et al., 2017), we stress that national power may play a stronger role under the uncertainty brought about by the epidemic. In terms of BITs, these treaties protect the basic interests of investors and provide relatively stable profit expectations for transferred multinationals and investments.

6. Necessary condition analysis

We have argued that institutional proximity augments the positive spillovers of Covid-19 shock in OFDI network, so that countries with OFDI and BIT linkages with the victim may receive more OFDI transfers from the RoW. However, this argument by itself is insufficient. Although we have mentioned the relationship among the Covid-19 victims, the partner-country of victims and the RoW, we still have to check whether multi-proximity promotes the formation of international OFDI network. Since the RoW tend to transfer its OFDI to the partners of the victimcountry, no matter it strengthens existing ties or establishes new ties, the necessary condition for the spillover effects of interest is that network global features (e.g. degree distribution) and network local features (e.g. assortativity) promote OFDI network formation(Granovetter, 1973).

Drawing on the analysis methods of existing research on the dynamic mechanism of network formation(Schoeneman et al., 2022), we

Table 3

The moderating effects of multi-proximity.

Matrix	Adjacency⊙Economic	Culture © Economic	Institution⊙Economic (3) OFDI_in	
	(1)	(2)		
Variable	OFDI_in	OFDI_in		
W*OFDI	0.072***	0.038***	0.058***	
	(9.44)	(5.88)	(7.95)	
L.OFDI	0.447***	0.449***	0.445***	
	(45.91)	(46.09)	(45.09)	
L.W*OFDI	-0.029***	-0.014**	0.027***	
	(-3.57)	(-2.13)	(3.57)	
shock	-0.073	-0.475**	-0.427*	
	(-0.27)	(-1.97)	(-1.75)	
W*shock	-0.719**	-0.188	2.640***	
	(-2.33)	(-0.55)	(5.39)	
SR Direct	-0.059	-0.451*	-0.407*	
	(-0.23)	(-1.95)	(-1.74)	
SR_Indirect	-0.621***	-0.170	2.480***	
-	(-2.63)	(-0.66)	(5.56)	
SR_Total	-0.680**	-0.620*	2.072***	
-	(-2.38)	(-1.85)	(4.10)	
LR_Direct	-0.108	-0.817*	-0.734*	
-	(-0.23)	(-1.95)	(-1.74)	
LR Indirect	-1.129***	-0.312	4.477***	
-	(-2.64)	(-0.67)	(5.54)	
LR_Total	-1.237**	-1.130*	3.743***	
-	(-2.39)	(-1.85)	(4.10)	
country FE	Yes	Yes	Yes	
time FE	Yes	Yes	Yes	
Observations	8968	8968	8319	
R-squared	0.189	0.188	0.159	
N	152	152	141	

Note: Z-statistics in parentheses. OFDI_in series are measured by residual terms. Using row-standardized matrices for estimation. \odot is matrix Hadamard production according to equation (E3). SR = short-run, LR = long-run. ***p < 0.01, **p < 0.05, *p < 0.1.

implement an ERGM (exponential random graph model) to account for the covariate determinants of OFDI network formation. A typical ERGM model is able to estimate the effect of network sub-structure on network formation(Hunter et al., 2008). Its expression is as follows:

$$\operatorname{logit}\left[P\left(Y_{ij}=1 \middle| n_actors, Y_{ij}^{c}\right)\right] = \sum_{k=1}^{\kappa} \theta_k \delta_{z^{k}(y)}.$$
(E4)

On the right-hand side of equation (E4), k represents the number of network sub-structures, κ represents the total number. θ_k is the corresponding coefficient of each network sub-structure, while δ_{kj}^k accounts for the change of network statistics when adding a connection between network nodes *i* and *j*.

We use a R package designed for ERGM to estimate the model, and record estimated coefficients in Fig. 3. These coefficients account for the contributions of certain network structures on global OFDI network formation. In Fig. 3(a), it is obvious that node degrees (measured by istar-3 and ostar-3) and the tendency to form investment blocs among countries (measured by triangle) significantly contribute to the formation of OFDI network. However, mutually beneficial relationship of OFDI among countries appears to be more important in network formation in year 2021. The results show that reciprocal investment and investment groups among countries may be important forms of coping with the uncertainty of the international market after the Covid-19 outbreak.

Moreover, Fig. 3(b) shows that cultural networks (e.g. language and religion proximity networks) and institutional networks (e.g. legal and BIT proximity networks) play important roles in OFDI network formation. Statistically speaking, only language proximity network and BIT network have significant signs in 2021, but the importance of language proximity on binding OFDI network has decreased. Although both of them are important factors in FDI location choice(Wang et al., 2021), the change of coefficient significance of BIT network covariate supports that national power may be much more prominent in the time of epidemic shock. This evidence further echoes that in the context of increasing

global economic uncertainty, hard institutional arrangements represented by investment agreements are more efficient in forming investment networks than relying solely on soft constraints of cultural similarity(Zheng et al., 2022). To conclude, we learn from the ERGM estimation that multi-proximity, especially BIT network, promotes the formation of international OFDI network. Such evidence, as a necessary condition, underpins our previous argument that Covid-19 shock has positive spillover effects in the global OFDI network.

7. Discussion and conclusion

Foreign direct investment has been widely regarded as an important factor in promoting economic growth, knowledge transfers, export upgrading and global integration. In recent years, greenfield direct investment has become an extreme prominent part of FDI. Driven by national will of the state and global profit-seeking strategies of multinationals, greenfield OFDI have tremendously contributed to resource extraction, production marketing, R&D activities and regional development. However, the outbreak of Covid-19 epidemic has greatly reshaped global OFDI landscape. Standing on the shoulders of previous works, this paper aimed to provide a study on the spillover effects of Covid-19 shock in OFDI network.

Overall, based on the network description and empirical results, it appears that the impact of the epidemic on global OFDI network is not as negative as we thought. First, although the number of OFDI projects has dropped sharply after the outbreak of Covid-19 epidemic, some countries have received more project inflows transferred from the rest of world, so that the global OFDI network has remained robust. Second, we have figured out that countries at the periphery of the OFDI network would be more likely to become the transfer destination. Third, in the uncertainty, inter-country institutional-proximity, measured by the BIT network, has been more important than geographical proximity and cultural similarity in promoting global OFDI network formation.

Our conclusions seem to be criticized by "hitting somebody when he

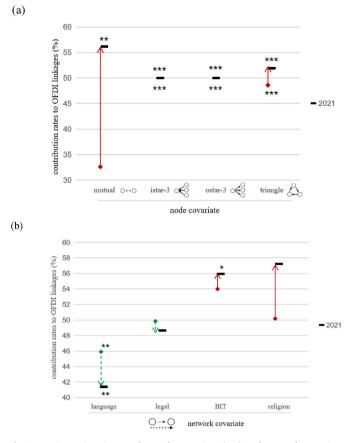


Fig. 3. ERGM estimation results: node covariate (top) and network covariate (bottom).

Note: the black bar represents estimated coefficients of 2021 global OFDI network. The red-solid or green-dash arrows represent the difference between the regression results in 2019 and the regression results in 2021, respectively. Circles and black solid lines represent network nodes and corresponding OFDI relationships between nodes (network sub-structures). When calculating the contribution rate, we control node attributes, such as national FDI dependence, industrial structure, GDP, population and land area. All contribution data are obtained by transforming the model estimation results through the logistic function. ***p < 0.01, **p < 0.05, *p < 0.1.

is down". However, what we have argued is neither a zero-sum game in international political economy(Bardazzi & Ghezzi, 2022), nor a preference for de-globalization(Abdal & Ferreira, 2021). On the contrary, through the network perspective, we have taken a open view to scrutinize into the trend of international OFDI flows under the background of the global epidemic. As mentioned by Ahmad et al. (2021), the Covid-19 epidemic has fueled FDI outflows and transfers. Although the global epidemic has seriously affected the attractiveness of most global economies, investment relocation would more or less defend the "black swan" in some countries(Ajide & Osinubi, 2020). For example, in recent years, Vietnam has undertaken a bunch of competitive manufacturing projects transferred from FDI partners such as the US, China, Japan and the Republic of Korea. Although the economy of this Southeast Asian country has been severely hit by the epidemic, Vietnam still attracted an additional US\$26.43 billion in registered FDI capital from January to November 2020.³ It should be noticed that our start point is that the outbreak of epidemic would augment OFDI reshoring rather than simply cause it. As mentioned by Truong (2022), no evidence reveals that the outbreak of COVID-19 in Vietnam has increased the outflow burden of its partners. The possible reasons could be that Vietnam has minimized quarantine stringency and expanded trade agreements networks. In this sense, our work has echoed Truong's viewpoint, addressing the importance of local policies and institutional bandages for developing countries in tightly participating in the world economy.

Our findings also shed a bright light on the development of world economy, especially on the economic development of the Global South, under the global public health shock. For many years, the southern countries have always been perceived as the place of poverty, backwardness, and global fringe. However, we would like to echo Horner and Nadvi (2018) that the rise of Global South and its embeddedness into global OFDI participation significantly benefit the whole economic network. In other words, if the southern countries continue to maintain an open attitude towards global cooperation, they are likely to stabilize the world economy and witness a gradual upgrading in the global OFDI network(Gómez et al., 2022).

Last but not least, we address our research limitations and caveats. First, our spatial econometric model only helps portrait the spillover effects of the epidemic as a whole, instead of identifying the role of OFDI substitution at a single-nation level. Therefore, future research should further identify specific geographic routines for global OFDI reshoring and relocating in the shock of Covid-19 epidemic. Second, our database only records the exact number of greenfield investment projects. So we regret not being able to show the whole picture of global OFDI from the binary margin. Third, cutting-edge research on complex networks has paid attention to the interconnected relationship between multiplex networks. However, we cannot estimate the joint impacts of trade, immigration, innovation and other networks on global OFDI spillovers. Future research needs to examine the impact of the epidemic on the global economic pattern from more sophisticated network perspectives.

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Author contributions

Hantian Sheng: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing.

Xiaomian Dai: Conceptualization, Methodology, Formal analysis, Data curation, Writing - Review & Editing,

Canfei He: Resources, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary materials

Supplementary materials to this article can be found online at https://doi.org/10.1016/j.apgeog.2023.102978.

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³ Relevant information comes from the report "Vietnam is ready to welcome FDI shift from China". Website: https://en.vietstock.vn.

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