Complex Dependence in Foreign Direct Investment: Network Theory and Empirical Analysis*

John Schoeneman† Boliang Zhu‡ Bruce A. Desmarais§

Abstract

We develop a theoretical framework that accounts for complex dependence in foreign direct investment (FDI) relationships. Conventional theories of FDI focus on firm-, industry-, country-, or dyad-level characteristics to account for cross-border capital movements. Yet, today's globalized economy is characterized by the increasing fragmentation and dispersion of production processes, which gives rise to complex dependence among production relationships. Consequently, FDI flows should be represented and theorized as a network. Specifically, we argue that FDI relationships are reciprocal and transitive. We test these hypotheses along with conventional covariate determinants of FDI using an exponential random graph model (ERGM) for weighted networks. We find that FDI networks exhibit strong reciprocity and transitivity. Our network approach to studying FDI provides new insights into cross-border investment flows and their political and economic consequences, and more generally the dynamics of globalization. In addition to our substantive findings, we offer a broad methodological contribution by introducing the ERGM for count-weighted networks in political science.

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† jbs5686@psu.edu, Visiting Assistant Professor, Oklahoma State University.

‡bxz14@psu.edu, Associate Professor, Department of Political Science, Pennsylvania State University.

§ bdesmarais@psu.edu, Associate Professor, Department of Political Science, Pennsylvania State University.

1 Introduction

What explains foreign direct investment (FDI) flows? Standard economic models attribute cross-border capital movements primarily to relative factor endowments, market size, and transportation and trade cost (Carr, Markusen and Maskus, 2001; Helpman, 1984). According to the eclectic theory of FDI (Dunning, 1988, 1992), multinational corporations (MNCs) arise from exploiting the advantages of internalizing firm-specific assets such as proprietary technology, marketing and advertising skills, and brand names; MNCs choose an investment location that allows them to best capitalize on their intangible assets. Building on the insight of the "obsolescent bargain" (Vernon, 1971, 1980), the political economy literature focuses on the role of domestic and international institutions in constraining host governments' predatory behavior and therefore in attracting FDI (e.g., Allee and Peinhardt, 2011; Büthe and Milner, 2008; Jensen, 2003, 2006; Kerner, 2009; Li and Resnick, 2003; Staats and Biglaiser, 2012). One common assumption in the extant literature is that FDI flows into one country or between one dyad are *independent* of other countries or dyads.[1]

Over the past decades, production processes have been increasingly characterized by fragmentation and dispersion of tasks and activities, which gives rise to global production chains and complex networks; at the center of global production networks are MNCs, who coordinate these networks through foreign affiliates, contractual agreements, and arm's-length transactions (UNCTAD, 2013). This is referred to as "globalization's 2^{nd} unbundling" that began in the 1980s (Baldwin, 2011). For example, Boeing has a relationship with 5,400 supplier factories throughout the world, employing about 500,000 people through its supply chain.[2] In Thailand's automobile industry, a group of 52 foreign affiliates, part of 35 business groups or MNC networks, produce 56% of total output; the network of the 52 for-

[1] Note that existing studies have examined the dependence of FDI (e.g., Baltagi, Egger and Pfaffermayr, 2007; Blanco, 2012; Blonigen, Davies, Waddell and Naughton, 2007; Coughlin and Segev, 2000). However, the dependencies that characterize the complete FDI network have not been studied yet. See more discussions in next section.

[2] "Our Supply Chain." Randy's Journal: A Boeing Blog. `https://randy.newairplane.com/2013/02/21/our-supply-chain/`, accessed April 11, 2018.

eign affiliates "comprises some 6,000 co-affiliates located in 61 countries around the world" (UNCTAD, 2013, 137).

When countries are interconnected by complex production networks, investment flows among states can no longer be understood simply as a result of an individual firm's decision to exploit its firm-specific assets or host countries' factor endowments. A country's ability to receive FDI hinges also on its connections to global production networks. If global FDI flows can arise endogenously from the network structure, conventional theories of FDI remain *incomplete* by excluding structural dependencies inherent to complex production networks.

We argue that two network structures—reciprocity and transitivity—are important to account for the pattern of cross-border FDI flows. Reciprocity is the tendency for the investment of country i in country j to be proportional to that of country j in country i, other factors held constant. We posit that reciprocity arises from the fact that existing MNCs help reduce the transaction costs of investing in their home country through diffusing information about their home-country environments, which is facilitated by the existence of global production networks. Therefore, FDI is more likely to flow from country i to country j if there is already a high stock of FDI from country j in country i.

Transitivity is the tendency for two countries that have strong investment ties to the same third country to have strong investment ties with each other (i.e., a friend of a friend is a friend). We argue that the transitivity of FDI arises from the expansion of global production networks and a safety net created by existing FDI linkages; The safety net protects firms from host governments' opportunistic and predatory behavior and increases the likelihood of FDI flows between two countries that have FDI ties with the same third country, thereby leading to the transitivity of investment activities.

To test our arguments, we use the count exponential random graph model (ERGM) to explicitly model interdependencies among FDI relationships between states (Krivitsky, 2012). The count ERGM is suitable for testing our argument for two reasons: (1) ERGM family models allow us to test precise hypotheses regarding dependent network structure, in

addition to including conventional covariates (Desmarais and Cranmer, 2017); (2) the count ERGM is capable of modeling zero inflation in the network, which is the dominant characteristic of bilateral FDI data. Utilizing bilateral FDI data from the United Nations Conference on Trade and Development (UNCTAD) over the 2001–2012 period, we find strong evidence that FDI flows are reciprocal and transitive (i.e., strongly clustered). These results suggest that cross-border FDI flows are *interdependent* and shaped by their network structure.

We make several important contributions to the literature. First, we advance the FDI literature by developing and testing a novel network theory. That is, FDI flows are determined by structures of interdependence—a class of generative processes that has been overlooked in the political economy of FDI literature that focuses heavily on domestic political institutions. FDI networks are not simply an error structure that needs to be modeled empirically, but also substantively important in explaining the pattern of cross-border investment movements. From the perspective of our network approach, a country's likelihood of receiving foreign investment depends not only on its own locational advantages such as factor endowments, market size, and institutional environments, but also on its connectivity to existing partner states in the network.

Second, understanding interdependence through FDI networks is critical to understanding the global economic system as a whole. Recent research on interdependence in the global financial system has documented economic contagion through international trade networks (Kali and Reyes, 2010), international lending (Oatley, Winecoff, Pennock and Danzman, 2013; Zakaria and Fatine, 2017), overlapping capital ownership (Chuluun, 2017), and networks established through currency exchange markets (Matesanz and Ortega, 2014). In the current paper we develop a model of the global FDI using a methodology that enables us to evaluate the ways in which an exogenous shock to one part of the network can have long-run effects on the global structure of the network (see more discussions in Section 4.2.).

Third, our article speaks to the "science and the system" debate in the International Political Economy (IPE) field (see, Chaudoin and Milner, 2017; Chaudoin, Milner and Pang,

2014; Cohen, 2008; Drezner and McNamara, 2013; Oatley, 2011). This debate centers on the relative importance of domestic versus systemic factors in accounting for the process of globalization. The dominant "Open Economy Politics" approach (Lake, 2009) in IPE has been criticized as the "reductionist gamble" because of its ignorance of system interdependence (Oatley, 2011). In this article, we consider both domestic and systemic factors simultaneously and show that the pattern of FDI flows is accounted for by both domestic factors and system interdependence. Our paper joins scholars' recent efforts of bringing in systemic factors to the studies of economic globalization (see, e.g., Cao and Ward, 2014; Chaudoin, Milner and Pang, 2014; Chaudoin and Wilf, 2018; Hafner-Burton, Kahler and Montgomery, 2009; Ward, Ahlquist and Rozenas, 2013).

Finally, to our knowledge, the count ERGM has not been applied previously in political science research. The count ERGM can be applied to any network in which ties are count-weighted, and therefore represents a valuable tool for political scientists, who regularly study networks with count-weighted ties (e.g., shared membership in international governmental organizations (Boehmke, Chyzh and Thies, 2016), the count of bills co-sponsored between legislators (Kirkland, 2013)).

We organize the paper as follows. In the next section we present theoretical claims that FDI flows can arise from its network dependence and the FDI flows exhibit reciprocity and transitivity. Then, we discuss the research design and the count ERGM and present empirical results. Finally, the paper concludes.

2 Dependence Hypotheses in FDI Flows

The extant FDI literature focuses on firm-, industry-, country-, or dyad-level parameters to explain cross-border investment flows. The eclectic paradigm suggests that MNCs arise from taking advantage of firms' intangible or specific assets to overcome imperfections in arm's-length transactions (Dunning, 1988, 1992). In general equilibrium models, firms undertake

direct investment to exploit relative factor endowments or to overcome transportation and trade costs (Carr, Markusen and Maskus, 2001; Helpman, 1984). The political economy of FDI literature starts with the premise that footloose capital becomes relatively immobile after investment takes place and thus it is vulnerable to government expropriation (Vernon, 1971, 1980). This literature therefore focuses on the role of domestic and international institutions in preventing states' predatory behavior and ensuring credible commitment, thereby attracting FDI (e.g., Allee and Peinhardt, 2011; Büthe and Milner, 2008; Jensen, 2003, 2006; Li and Resnick, 2003; Staats and Biglaiser, 2012).[3]

One common, though not without exception, assumption in existing theoretical and empirical models is that FDI flows into one country or within one dyad are independent of other countries or dyads. The exception to assuming independence is found in the line of monadic studies of FDI that model spatial dependence. These studies include, for example, Coughlin and Segev's (2000) analysis of province-level FDI in China, in which they found a high degree of spatial autocorrelation in annual FDI; Blanco's (2012) analysis of country-level FDI in Latin America, in which she finds that FDI in a country is related to the market potential in surrounding countries; and Baltagi, Egger and Pfaffermayr's (2007) and Blonigen et al.'s (2007) analysis of outbound FDI from the U.S., in which they document both spatial autocorrelation and effects of third-country market potential and relative factor endowments. The last two examples (i.e., Baltagi, Egger and Pfaffermayr, 2007; Blonigen et al., 2007) are technically dyadic data, but also has a monadic form since there is one observation per country in each year. Though spatial dependence is an important feature of monadic FDI, spatial approaches are limited in that they address one form of interdependence—spatial autocorrelation. As we elaborate below, dependencies in FDI can take on a number of other structural forms. Metulini, Patuelli and Griffith (2018) develop a spatial model for dyadic data that would be quite appropriate for dyadic FDI, as it adjusts for zero inflation. However, the model they develop does not estimate dependencies directly. Rather, they develop a method

[3]See Pandya (2016) for a comprehensive review of the literature.

to filter out sender, receiver, and network sources of autocorrelation. The network analytic approach that we propose permits the researcher to directly estimate and test hypotheses about virtually any form of dependence that can be theorized. We seek to build upon the progress made in understanding spatial dependence in FDI by studying forms of dependence that characterize the complete network of FDI connections among countries. Given the intertwined linkages among MNCs and the expansion of global production networks (Baldwin, 2011; UNCTAD, 2013), we expect that high-order network structures should play an important role in shaping the pattern of FDI flows as well.

2.1 Reciprocity of FDI Flows

Reciprocity has been long studied in the international relations literature as a strategy to achieve international cooperation under anarchy (e.g., Axelrod, 1984; Keohane, 1984). It is well known that international trade is conducted based on the principle of reciprocity under the GATT/WTO regime in the sense that governments lower tariffs reciprocally to neutralize the terms-of-trade externality (Bagwell and Staiger, 1999). Reciprocity embedded in traditional bilateral investment treaties (BITs), however, concerns more the equal treatment and protection of investors, not liberalization or exchanges of market opportunities (DiMascio and Pauwelyn, 2008, 56).

Conventional dyadic models of FDI flows typically imply reciprocity. The institutional and cultural distance literature suggests that FDI is more likely to flow between a pair of countries that are institutionally and culturally similar, share common languages and colonial ties, and are in an alliance relationship or tied by migrant networks (e.g., Beazer and Blake, 2018; Eden and Miller, 2004; Leblang, 2010; Li and Vashchilko, 2010). Note that this type of reciprocity is based on covariates. Existing literature has not yet studied the reciprocity arising from the interdependence of the *outcome* variable itself. That is, FDI from country i to country j increases the probability of investment from country j to country i.

We argue that the reciprocity of FDI stems from the fact MNCs act as agents of trans-

mitting information about their home countries, which is facilitated by the existence of global production networks; The information diffusion helps to reduce host-country firms' transaction costs of investing in MNCs' home countries, thereby increasing the likelihood of reciprocal flows of investment. Investing in a foreign country incurs a "liability of foreignness." Foreign firms faces disadvantages compared with indigenous firms because the former are unfamiliar with the business practices and institutional environments and face a legitimacy issue due to greater scrutiny from the public in the host country (Hymer, 1976; Kostova and Zaheer, 1999; Zaheer, 1995). This unfamiliarity and legitimacy issue induces extra business costs that often deter foreign entry. Existing MNCs actually help diffuse information about business practices and institutional environments in their home country (Kwok and Tadesse, 2006; Sandholtz and Gray, 2003; Simmons and Elkins, 2004). This kind of information diffusion is particularly strong in the existence of global production networks. For example, it can happen within MNC's global production networks via vertical linkages to their upstream suppliers and downstream customers. More generally, information diffusion can occur through the spillover of knowledge and management know-how from MNCs to local firms. Consequently, local firms in the host country acquire more information about investment opportunities, business practices, government policies, and so on, thereby reducing information asymmetry and the liability of foreignness when investing in MNCs' home country.[4] All else being equal, we therefore should expect that firms in country i are more likely to invest in country j if firms from country j hold a high stock of investments in country i.

Hypothesis 1: FDI flows are reciprocal.

An old literature has studied MNCs' oligopolistic expansion strategy (Hymer, 1976; Kindleberger, 1969), which can also result in the reciprocity of FDI. MNCs arise from exploiting their firm-specific assets to overcome imperfections in arm's-length markets (Caves,

[4]Leblang (2010) suggests that diaspora networks promote investment from host to home countries as they help reduce the transaction and information costs of host country firms investing in their home countries.

1996; Dunning, 1992). These proprietary assets include, for example, advanced technology, brand names, product differentiation, and managerial and advertising skills, which possess substantial economies of scale. To make the most use of their firm-specific assets and best exploit economies of scale, MNCs actively seek to expand market shares. Yet, an MNC's successful expansion into a foreign market generates disruptive effects, threatening the market positions of local firms. To secure their competitive positions and obtain advantages stemming from large-scale operations, local firms have incentives to undertake a rivalrous expansion with highly differentiated products into the home market of the MNC (Veugelers, 1995).[5] This rivalistic strategy leads to reciprocal flows of FDI (Graham, 1978). We expect this kind of reciprocal FDI flows is more prevalent among developed countries because they are primarily market seeking and firms in developed countries have accumulated sufficient intangible assets that enable them to succeed in foreign markets.

Historically, global investment activities have been dominated by MNCs from developed countries and characterized by a pattern of two-way flows (Julius, 1990, 22). While this means reciprocity has been conditional on the level of development of the states in a dyad, the patten has been changing. On the one hand, developing countries become increasingly popular investment destinations. In 2012, developing countries as a whole received more FDI than developed countries for the first time ever (UNCTAD, 2013). On the other hand, we have also witnessed a surge of FDI from, and increasingly between, developing countries since the beginning of the 21^{st} century. The percentage of outward FDI from developing and transition economies has grown from 8.78% in 2001 to 29.42% in 2017, with a peak in 2013 (approximately 35.54% of the world total). Yet, investing abroad incurs large fixed costs and firms need to overcome the disadvantages such as liability of foreignness they face when competing with indigenous firms in the host country. Therefore, only the most productive firms are able to engage in FDI activities (Helpman, Melitz and Yeaple, 2004).

[5]Such a rivalrous expansion is likely to occur when two conditions are met: (1) local firms possess intangible assets that enable them to exploit rents in the foreign market; (2) their entry could disrupt the home market of the foreign firm (Graham, 1978).

Given that MNCs from developing countries are still smaller and less competitive than their counterparts from developed countries, we expect that developing countries are less likely to reciprocate FDI. In our empirical analysis, we explicitly model this actor heterogeneity.

2.2 Transitivity/Clustering of FDI Flows

Transitivity, sometimes referred to as clustering, would manifest as dense triads of FDI emerging in the FDI network. We argue that the transitivity of investment activities arise from the expansion of global production networks and a safety net created by existing FDI linkages. One distinct feature of today's globalization is the increasing fragmentation and dispersion of production processes and the dramatic expansion of global supply chains (Baldwin, 2011; UNCTAD, 2013). At the center of global production networks are MNCs, which coordinate global supply chains through complex networks of their foreign affiliates, subcontractors, or arm's-length suppliers (UNCTAD, 2013, xxii). These intertwined production networks give rise to the transitivity of FDI activities.

In a direct way, an MNC's establishment of foreign affiliates will be followed by investment of their upstream suppliers or downstream customers, who have also invested in the MNC's home country. This type of production connections will lead to multiple triadic closures of investment flows. Consider a case of three countries: A, B, and C. Suppose a firm from A invests in B as a supplier to a firm in B. If the firm in B establishes a foreign affiliate in C, the firm from A likely follows and makes an investment in C to serve the foreign affiliate, thereby leading to a triadic closure of investment flows.

Note that suppliers do not necessarily need to undertake an overseas investment to serve a leading firm. Alternatively, suppliers can choose to export intermediate goods to a leading firm. Yet, the aforementioned triadic closures of investment flows are not uncommon because leading firms tend to favor near suppliers due to an industry clustering effect or high transportation and trade costs (Carr, Markusen and Maskus, 2001). For example, Volkswagen's investment in Skoda Auto in Czech Republic not only attracted other auto makers such as

PSA Peugeot and Toyota, but also its international suppliers of parts and components to acquire local firms or build new factories; "As of 2002, there were 270 firms operating in the Czech Republic, representing 45 percent of the top 100 world suppliers of automotive parts and components" (Kaminski and Javorcik, 2005, 352). Likewise, Volkswagen's recent investment in Ningbo-Hangzhou Bay New Zone in China has brought in suppliers from South Korea, France, and the United States.[6] Airbus's establishment of its A320 assembly line in Tianjin, China has attracted investments from its global suppliers to the Tianjin Airport Economic Zone and contributed to an aviation industry cluster with an output estimated to exceed 100 billion Chinese yuan in 2020.[7] In India, investments by auto makers such as Toyota, Hyundai, and Ford also brought in their international component suppliers (Moran, 2014, 23).

More generally, when two countries are tied to a third country via FDI, these FDI linkages create a safety net that protects MNCs from host governments' opportunistic and predatory behavior and thus facilitate capital movements between these two countries, thereby resulting in a triadic closure of investment flows (i.e., the transitivity of FDI). Although direct asset expropriation has been rare since the late 1970s, political risk such as subtle policy changes remains a primary concern of investors (Graham, Johnston and Kingsley, 2018), because footloose capital becomes an "obsolescent bargain" due to its ex post immobility (Vernon, 1971, 1980). When two countries are connected to a third country via FDI, which typically involves the expansion of global production networks, it significantly constrains governments' policy discretion. This is because the proper functioning of global production networks hinges crucially on the cooperation and coordination of the countries involved. For example, Johns and Wellhausen (2016) show that host governments are less likely to expropriate foreign firms when they are closely connected to firms in host countries through supply chains. Dorussen

[6]Hangzhou Bay New Zone, "Shanghai Volkswagen Ningbo Base of Suppliers Area and Ningbo International Automobile (Parts) Industrial Park Promotion Conference Held in Shanghai." Retrieved from `http://cepz.ningbo.gov.cn/cat/cat159/con_159_5310.html`. Accessed June 7, 2017.

[7]Bo Jin, "*Yitiao Zongzhuangxian, Qianyi Chanyelian* [One Assembly Line, A 100 Billion Industry Chain]," *People's Daily*, September 25, 2017.

and Ward (2010) demonstrate that countries are less likely to have conflicts with each other when they are more embedded in the trade networks. Likewise, Kim and Solingen (2017) find that East Asian countries that are deeply integrated into global production networks are more likely to promote cooperation and peace between each other.

This risk-mitigating effect of the safety net is magnified when two countries are integrated into the same global production networks coordinated by leading MNCs in a third country. Consider an example that MNCs in Country A offshore their production or other operating activities via FDI to Countries B and C; local firms in Countries B and C may also be integrated into these production networks as either upstream suppliers or downstream customers. In such a case, all three countries have strong incentives to ensure the well functioning of the network for economic benefits and thus are less likely to engage in opportunistic or predatory behavior, thereby providing a safety net for investors. Consequently, firms in Countries B and C are also more likely to invest in each other, contributing to the transitiveness of FDI.[8] In general, when two countries are tightly linked to a third country through investment flows, FDI should be more likely to flow between these two countries due to shared economic interests and reduced political risk. That is, a friend of a friend is a friend. Therefore, we expect that FDI has a high probability to flow among two countries that have strong investment ties to the same third country, resulting in the transitivity/clustering of investment activities.

Hypothesis 2: FDI flows are transitive.

It is important to note that our theory suggests that the reciprocity and transitivity of FDI is not a result of the global bilateral tax treaty (BTT) networks or the existence of tax

[8]Note that direct investment is only one of the strategies that MNCs use to expand their global production networks. Alternatively, MNCs in Country A may choose to purchase intermediates goods from firms in Countries B and C. In such a case, both Countries B and C are also integrated into the global production networks coordinated by leading MNCs in Country A. As such, we would expect that FDI is more likely to flow between Countries B and C due to common economic interests and reduced political risk. Yet, it does not necessarily create a triadic closure of investment flows unless we also observe FDI flows from Country A to Countries B and C along with the FDI in either direction between Countries B and C.

havens.[9] Scholars have studied the implications of global BTT networks and tax havens for MNCs to create complex corporate structures for tax avoidance (e.g., Arel-Bundock, 2017*b*). For example, Google's "Double Irish Dutch Sandwich" corporate structure helped lower the company's effective tax rate to 2.4% on non-U.S. income.[10] This corporate structure results in complex financial flows between the parent company and its foreign affiliates and among foreign affiliates themselves. Yet, a complex single-firm corporate structure or financial flows within the corporate structure do not lead to the reciprocity and transitivity of FDI. This is because investments from the parent company to its foreign affiliates are one-way flows and profits repatriation and interest, dividends or royalties payments within the corporate structure are not registered as FDI (see, Kerner, 2014).

3 Data and Research Design

To test our hypotheses, we estimate a gravity model of FDI. The dependent variable is bilateral FDI stock.[11] The data are from UNCTAD, covering the time-period of 2001 to 2012.[12] Most existing empirical studies on FDI use monadic data because scholars are primarily interested in how host countries' economic and political characteristics affect capital inflows.[13] The advantage of using dyadic data is that it allows us not only to model network relationships, but to measure changes in FDI flows related to covariates that are at the dyad level, such as bilateral investment treaties (BITs), alliances, and bilateral trade. Following

[9]The existence of tax havens may inflate the reciprocity and transitivity of FDI. Our results are robust and consistent when we exclude tax havens in the sample. See detailed discussions in Appendix F.

[10]Jesse Drucker. "Google 2.4% Rate Shows How $60 Billion Is Lost to Tax Loopholes." *Bloomberg*. October 21, 2010. `https://www.bloomberg.com/news/articles/2010-10-21/google-2-4-rate-shows-how-60-billion-u-s-revenue-lost-to-tax-loopholes` (Accessed February 13, 2019.)

[11]We use FDI stock data because the count ERGM currently cannot model negative values in the dependent variable. By using stocks we minimize changes in the data by our transformation of negative values to zero, since negative FDI stock is rare as it only occurs when debt to a parent company exceeds FDI stock value. We also include a lagged dependent variable so that the model captures yearly changes of FDI stock (i.e. FDI flows) in the host country.

[12]Systematic bilateral FDI data are not available for earlier time periods. After subsetting for available covariates we are left with 124 countries. Every year has the same countries.

[13]There are very few studies that use dyadic FDI data. See, e.g., Leblang (2010), Li and Vashchilko (2010), and Razin, Sadka and Tong (2005).

common practice (e.g., Bénassy-Quéré, Coupet and Mayer, 2007; Hyun, 2006), we take the natural log of the FDI stock variable (adding 1 before logging). After logging, we multiply the logged values by two to reduce variation lost in the values in the final step of rounding to the nearest integer. This transformation is designed to (1) reign in the extreme outliers present in FDI stock data, and (2) construct a variable that can be modeled as a count while preserving variation.

The steps in this transformation are a matter of methodological necessity. The defining distributional feature of FDI data is zero-inflation, with there being an FDI stock of zero associated with 80–90% of directed dyads each year. We know of two models that can currently be used to model weighted network data with zero-inflation. The first is the latent space model developed by Ward, Ahlquist and Rozenas (2013) for modeling dyadic international trade with an excess of zeros. Unfortunately, we cannot use this model to test our dependence hypotheses, since it does not permit the inclusion of structural dependence terms. The other is the count ERGM (Krivitsky, 2012), which requires dependent variable values be positive integers. A number of other models are available in the literature that could be used to evaluate dependence hypotheses and model FDI on a continuous scale if they were extended to account for zero-inflation. These include the generalized exponential random graph model (GERGM) (Wilson, Denny, Bhamidi, Cranmer and Desmarais, 2017), the "AMEN" latent factor model (Minhas, Hoff and Ward, 2019), and the spatial modeling specifications proposed by Neumayer and Plümper (2010). We see modeling FDI stocks on the discretized logarithmic scale, as opposed to the more common continuous logarithmic scale, as an acceptable loss of information since it enables us to directly model the prevalence of zeros in the data, and to precisely test our dependence hypotheses. In Appendix B we show that rounding the logged value of FDI does not significantly change the correlation between FDI and any of the dyadic covariates that we include in the count ERGM.

The bilateral FDI data are collected mainly from national sources with technical assistance from UNCTAD; in cases where data are not available from host countries, UNCTAD

uses data from partner countries (mirror data) as well as from other international organizations.[14] One challenge of using bilateral FDI data is the large number of unreported values. The missing values seem likely to be zero or a negligible amount (and thus not truly missing, but unreported because there was nothing to report). Comparing a country's total FDI to the sum of bilateral FDI for each year, we find that in most cases the difference is small and likely due to rounding, centering around zero (see Figure A in Appendix A). Therefore, for our main models we impute the missing values with zeros so that we have a complete data set to model network dependence. In Appendix E, we present results using an alternative approach—subsetting to sets of countries on which we have more complete data, a common approach in dyadic research in political economy (e.g., Cao and Ward, 2014; Pettersson and Johansson, 2013). Our main findings regarding the effects of transitivity and reciprocity are robust to this alternative approach.

3.1 Covariates

In the gravity model, we include the log product of the dyad's real GDP and logged Euclidean distance. Generally, higher GDP represents a larger market and therefore should be associated with more FDI, while an increase in geographic distance increases investment costs, decreasing investment flows. For the purpose of model convergence, the logged product of dyadic GDP has been estimated as one variable in the model, rather than being estimated separately. In addition, we include both origin and destination countries' GDP per capita to roughly control for relative factor endowments.[15]

Other economic controls include origin and destination countries' trade openness (trade as % of GDP) and bilateral trade volumes between the origin and destination countries. Existing research has shown that FDI and trade are compliments (Aizenman and Noy, 2006; Markusen, 1995). We expect that higher levels of trade openness and bilateral trade will

[14] James Zhan. 2014. "Bilateral FDI Statistics." `http://unctad.org/en/Pages/DIAE/FDI%20Statistics/FDI-Statistics-Bilateral.aspx`, accessed April 11, 2017.

[15] Our GDP data are from the *Penn World Table*.

be associated with higher levels of bilateral FDI. Trade openness data are from the World Bank's *World Development Indicators* and trade volume is from the OECD (2016).

There is a substantial amount of work that explores the relationship between democratic institutions and FDI inflows; yet empirical results to date remain inconclusive (see, e.g., Arel-Bundock, 2017*a*; Busse and Hefeker, 2007; Jakobsen and De Soysa, 2006; Jensen, 2003; Li, Owen and Mitchell, 2018; Wright and Zhu, 2018). We include standard polity scores as a measure of a country's level of democracy (Marshall and Jaggers, 2010). We also include three international institutions variables: BITs, PTAs, and OECD membership. BITs are included as a binary variable that is one if the pair have a stand alone BIT or are party to a preferential trade agreement that also covers investment policy. These treaties should be positively associated with FDI levels as they should effectively remove barriers to investment and provide commitment to liberal economic policies (e.g., Allee and Peinhardt, 2011; Büthe and Milner, 2008; Medvedev, 2012; Osnago, Rocha and Ruta, 2016). PTAs vary significantly in depth with some requiring nearly full liberalization of trade barriers while others are superficial political signals. Therefore we make use a recent PTA depth variable that uses latent trait analysis with 48 different dichotomous variables regarding topics covered in PTAs.[16] Signing a PTA represents a commitment to liberal markets that investors would favor and therefore would be associated with increased FDI inflows (Büthe and Milner, 2008; Büthe and Milner, 2014). OECD membership is included as a binary node-level variable that is one when both countries are either OECD members or both are not OECD members. This variable adjusts for OECD-based homophily and is expected to be positive.

In addition, we include two sets of international agreement variables. The first is a binary variable for a combination of military alliance treaties that are not defense treaties. The second is a defense treaty. Both are from Gibler (2009). We expect these variables to be positively associated with FDI inflows, particularly defense treaties since this indicates

[16]PTA variable is from Dür, Baccini and Elsig (2014).

political cooperation and low political risk (Li and Vashchilko, 2010).[17]

3.2 Model and Specification: The Count ERGM

Like other forms of the ERGM, the count ERGM is a statistical model that operates on a complete network. To specify the count ERGM, the researcher selects two types of network statistics—those that relate tie values to observed covariates (i.e., covariate effects), and those that relate the ties to each other via higher-order network structure (i.e., network effects). The ERGM family of models is innovative in that both of these statistic types—covariate effects and network effects, can be included in the same model. Including the network effects helps to accurately identify the true covariate effects (Metz, Leifeld and Ingold, 2018). Under Krivitsky's (2012) count ERGM, the probability of the observed $n \times n$ network adjacency matrix $\boldsymbol{y}$ is

$$\Pr_{\boldsymbol{\theta};h;\boldsymbol{g}}(\boldsymbol{Y} = \boldsymbol{y}) = \frac{h(\boldsymbol{y})\exp(\boldsymbol{\theta} \cdot \boldsymbol{g}(\boldsymbol{y}))}{\boldsymbol{\kappa}_{h,\boldsymbol{g}}(\boldsymbol{\theta})}, \tag{1}$$

where $\boldsymbol{g}(\boldsymbol{y})$ is the vector of network statistics used to specify the model, $\boldsymbol{\theta}$ is the vector of parameters that describes how those statistic values relate to the probability of observing the network, $h(\boldsymbol{y})$ is a reference function defined on the support of $\boldsymbol{y}$ and selected to affect the shape of the baseline distribution of dyadic data (e.g., Poisson reference measure), and $\boldsymbol{\kappa}_{h,\boldsymbol{g}}(\boldsymbol{\theta})$ is the normalizing constant.

3.2.1 Specification

In the models we specify, we use statistics that model the shape of the individual edge distributions (i.e., the shapes of directed dyadic FDI flows), model the dependencies we have described above, and account for the effects of exogenous covariates. Network statistics in an ERGM model local dependencies, just like conventional covariates, but are expressed at the network-level because that is how they are incorporated into the ERGM probability distribution (Desmarais and Cranmer, 2012). Analogous to selecting covariates to include

[17] Summary statistics and a correlation matrix of the covariates are provided in Appendix A.

in a regression model, ERGM software packages present several options for adding network statistics to the model. Also, pragmatically speaking, we are somewhat limited by the availability of statistics in the ERGM software, as adding new network terms represents a non-trivial complex programming task. Indeed, according to the Hammersley-Clifford Theorem (Hammersley and Clifford, 1971), the probability distribution of any random graph can be represented as an ERGM (Yang, Rinaldo and Fienberg, 2014). The tasks of applied network modeling included discovering and implementing the correct specifications for a given network. The statistics we use to account for the individual edge distribution include (1) the sum of edge values, which models the average edge value; (2) the sum of square-root values of edges, which accounts for dispersion; and (3) the number of non-zero edges, which accounts for the prevalence of zeros in the edge values.

We include two statistics to model the dependencies that correspond to our hypotheses. First,

$$\text{Reciprocity} : \boldsymbol{g(y)} = \sum_{(i,j)\in\mathbb{Y}} min(\boldsymbol{y}_{i,j}, \boldsymbol{y}_{j,i}),$$

in which we add up the lowest edge value within each dyad. If edges are reciprocated, this statistic will increase due to the co-occurrence of large edge values within the same dyad. To evaluate our hypothesis regarding the higher degree of reciprocity among developing countries, we fit two separate reciprocity terms—one that applies to dyads in which both states are OECD members, and one that applies to every other dyad (i.e., both non-OECD, and mixed dyads that include an OECD and non-OECD state). [18] Second,

$$\text{Transitive Weights} : \boldsymbol{g(y)} = \sum_{(i,j)\in\mathbb{Y}} \min\left(\boldsymbol{y}_{i,j}, \max_{k\in N}\Big(\min(\boldsymbol{y}_{i,k}, \boldsymbol{y}_{k,j})\Big)\right),$$

which accounts for the degree to which edge (i, j) co-occurs with pairs of large edge values with which edge (i, j) forms a transitive (i.e., non-cyclical) triad with weighted, directed two-

[18] To do this, we updated the ERGM software package with a user term that conditions reciprocity on edge covariates for count models.

paths going from nodes i to k to j. Exogenous covariates are accounted for with statistics that measure the degree to which large covariate values co-occur with large edge values. First,

$$\text{Dyadic Covariate} : \boldsymbol{g}(\boldsymbol{y}, \boldsymbol{x}) = \sum_{(i,j)} \boldsymbol{y}_{i,j} x_{i,j},$$

measures this co-occurrence at the level of the directed dyad, in which there is a dyadic observation of the covariate corresponding to each potential FDI flow. There are two statistics that account for node (i.e., country) level covariates. Each statistic takes the product of the node's covariate value and a sum of the edge values in which the node is involved. The first, "Sender Covariate," uses the sum over the edges that the node sends. The second, "Receiver Covariate," uses the sum over the edges that the node receives.

We use the count ERGM implementation of Krivitsky's (2012) made available in the `ergm.count` (Krivitsky, 2016) package in the `R` statistical software. The normalizing constant in the likelihood function for the count ERGM (i.e., the denominator in Equation (1)) is given by

$$\boldsymbol{\kappa}_{h,\boldsymbol{g}}(\boldsymbol{\theta}) = \sum_{\boldsymbol{y} \in \boldsymbol{\mathcal{Y}}} h(\boldsymbol{y}) \exp(\boldsymbol{\theta} \cdot \boldsymbol{g}(\boldsymbol{y})),$$

where $\boldsymbol{\mathcal{Y}}$ is the set of all possible count network configurations, and $h(\boldsymbol{y}) = \prod_{i,j} (y_{i,j}!)^{-1}$ is the Poisson reference measure, which assures that (1) the normalizing constant is a convergent sum, and (2) produces an edge-wise conditional Poisson distribution if there are no dependence terms in the model. As with the binary ERGM, the normalizing constant in the count ERGM is computationally intractable, and must be approximated. Estimates of $\boldsymbol{\theta}$ are calculated using Monte Carlo maximum likelihood (MC-MLE). For more details on MC-MLE, see Snijders (2002).

We estimate a separate model for each year from 2002 to 2012. We have two main reasons for presenting year-by-year estimates as our main results. First, since analyzing dyadic data essentially squares the size of the data when compared to the monadic level, we have enough data to identify a separate set of parameter values in each year. Second, recent international

relations applications have called into question the appropriateness of pooling over long time periods since there may be considerable historical heterogeneity in the parameter values, and have estimated separate models for each year or time period (see, e.g., Cranmer, Heinrich and Desmarais, 2014; Ward and Hoff, 2007). In the results we present below, we see that many of the parameters vary considerably over time. In particular, several parameters exhibit significant shifts in magnitude and statistical significance beginning in 2008—a pattern that is likely attributable to the Great Recession. We present time-pooled results in Section C in Appendix.

4 Results

Throughout the results section, we compare two specifications of the count ERGM—one that assumes conditional independence among the edge values (i.e., the independence model), and the full specification that includes dependence terms. The only two terms that are excluded from the independence model are the reciprocity and transitivity terms. Before discussing individual effects, we first assess the relative fit of the independence and network models. The objective in this fit comparison is to summarize the fit contribution of adding the dependence effects to the model. Figure 1 presents the difference in Bayesian Information Criterion (BIC) between the independence and network models for each year in our analysis. We see that the BIC in the independence model is higher than that in the network model for each year, which provides robust evidence that the network model is a better fit for the data than the independence model over the time period that we study.[19]

To further investigate how the network model fits better, we compare simulated networks from the two models to the observed networks along four dimensions and for each year—a standard approach to evaluating the goodness of fit of network models (Hunter, Goodreau and Handcock, 2008). We present quantities that evaluate the fit of the models to the

[19]One additional consideration with ERGMs regards model degeneracy, based on which nearly all networks drawn from the model will be either completely connected or empty. The models we present are not degenerate.

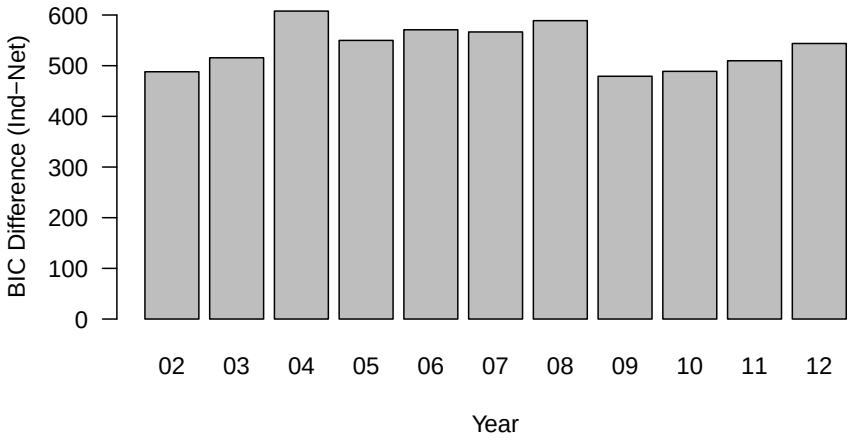

Figure 1: Difference in BIC between independent and network model.

reciprocity, transitivity, sender heterogeneity, and receiver heterogeneity of the networks. To measure the fit of the reciprocity, we use the weighted reciprocity measure proposed by Garlaschelli and Loffredo (2004)—the correlation between the weights of edges within the same dyads. This measure ranges between -1 and 1, with higher values corresponding to a greater degree of reciprocity. The measure we use to measure weighted transitivity comes from Opsahl and Panzarasa (2009)—the ratio of total transitive triple weights to total two-path weights, where the weight of a configuration is defined as the minimum value within the configuration. This measure ranges between 0 and 1, with larger values corresponding to more transitive network. To measure receiver and sender heterogeneity, we follow Minhas, Hoff and Ward (2019) and consider the variance (presented as standard deviations) in the total received (i.e., indegree) and total sent (i.e., outdegree) by each node.

We see in Figure 2 that the network model provides a much better fit to the observed network than does the independent model. The boxplots depict the network statistics computed on 100 networks simulated from each model in each year. The network model fits the reciprocity and transitivity in the observed network quite well, and consistently better than does the independence model. The network model generally fits the indegree standard deviation well, but in some years the independent model provides a better fit. The

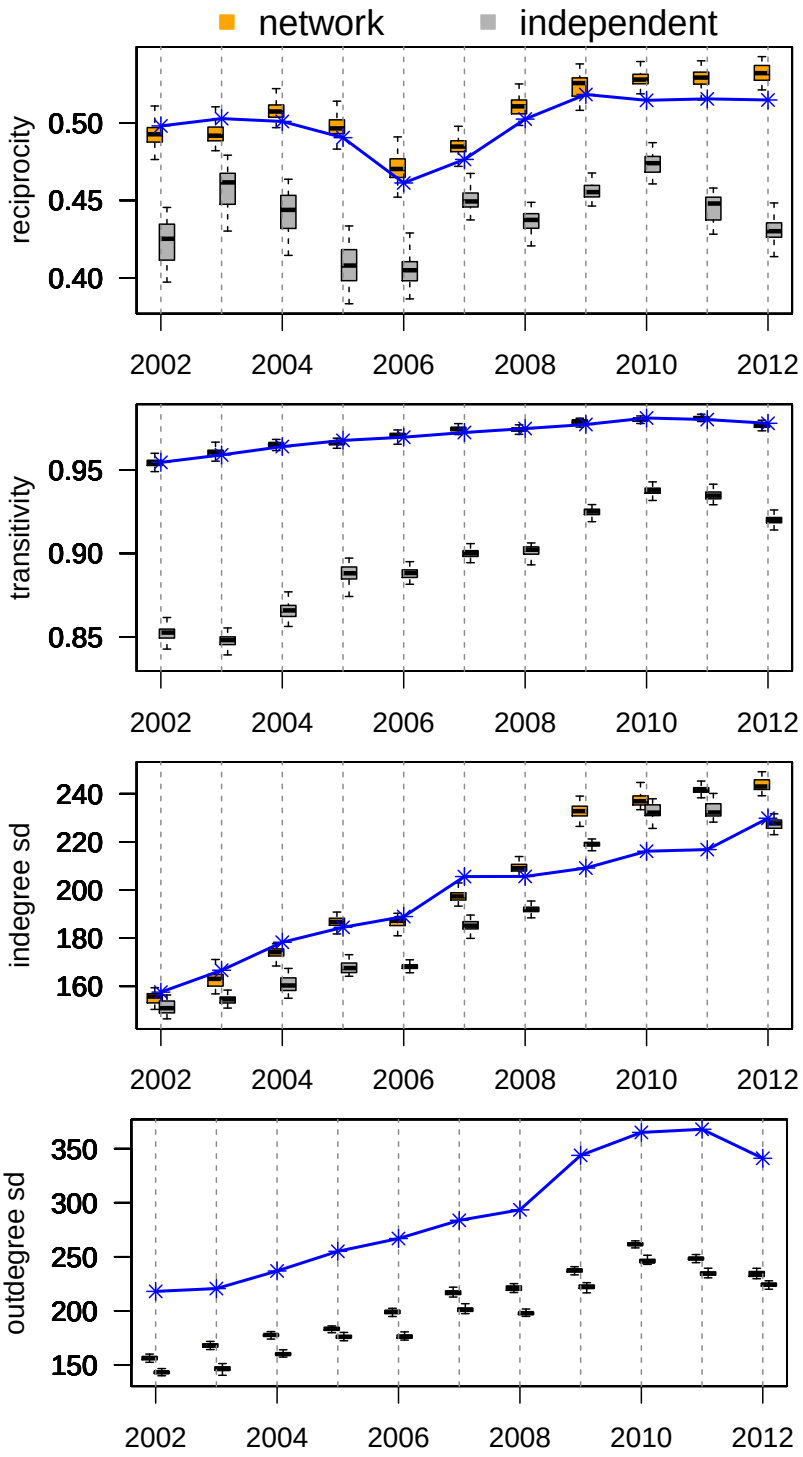

Figure 2: Structural fit of the network and independence models. Boxplots depict distributions over 100 simulated networks. The orange boxplots (those to the left of the dashed vertical lines), depict distributions from the full network model. The gray boxplots depict distributions from the independence models. The blue-starred lines give the observed values.

one statistic that is not fit very well with either model is the outdegree standard deviation. Unfortunately, the specifications available for modeling the degree distributions in the count ERGM are still rather limited. The two statistics currently available to model degree heterogeneity—the covariance and square-root-covariance of edge values sent or received by the same node, exhibited degeneracy when fit to the FDI networks. The development of less degeneracy-prone degree statistics, such as the geometrically weighted degree terms available for binary ERGMs (Snijders, Pattison, Robins and Handcock, 2006), is an important avenue for future research with the count ERGM.

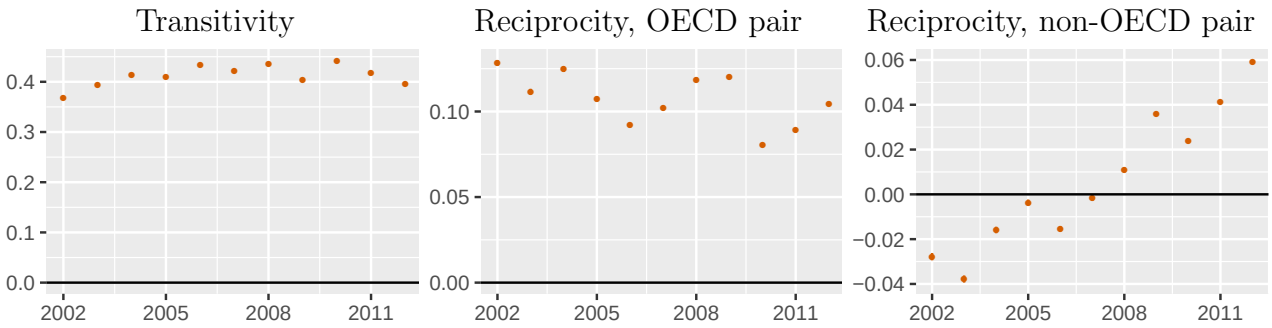

Figure 3: Estimates of network terms in Poisson ERGMs. Bars span 95% confidence intervals. The confidence intervals are not visible due to being small and the large range.

Turning now to the findings regarding network effects, which are presented in Figure 3, we see that the transitivity effects are positive and statistically significant in each year. Additionally, reciprocity is significant and positive in every year for OECD pairs and for non-OECD pairs the coefficient is gradually converging to that of OECD pairs. This convergence of coefficients for reciprocity is consistent with our expectation that reciprocity is prevalent among developed countries and developing countries have begun to reciprocate FDI. It illustrates that reciprocity characterizes the entire FDI network, not just highly developed countries. Generally, these results offer robust evidence that FDI flows are interdependent according to these two canonical forms of network structure. While these forms of network dependence are common in networks, they are not inherent and therefore this finding is significant and as substantively important as findings regarding conventional exogenous

covariates.

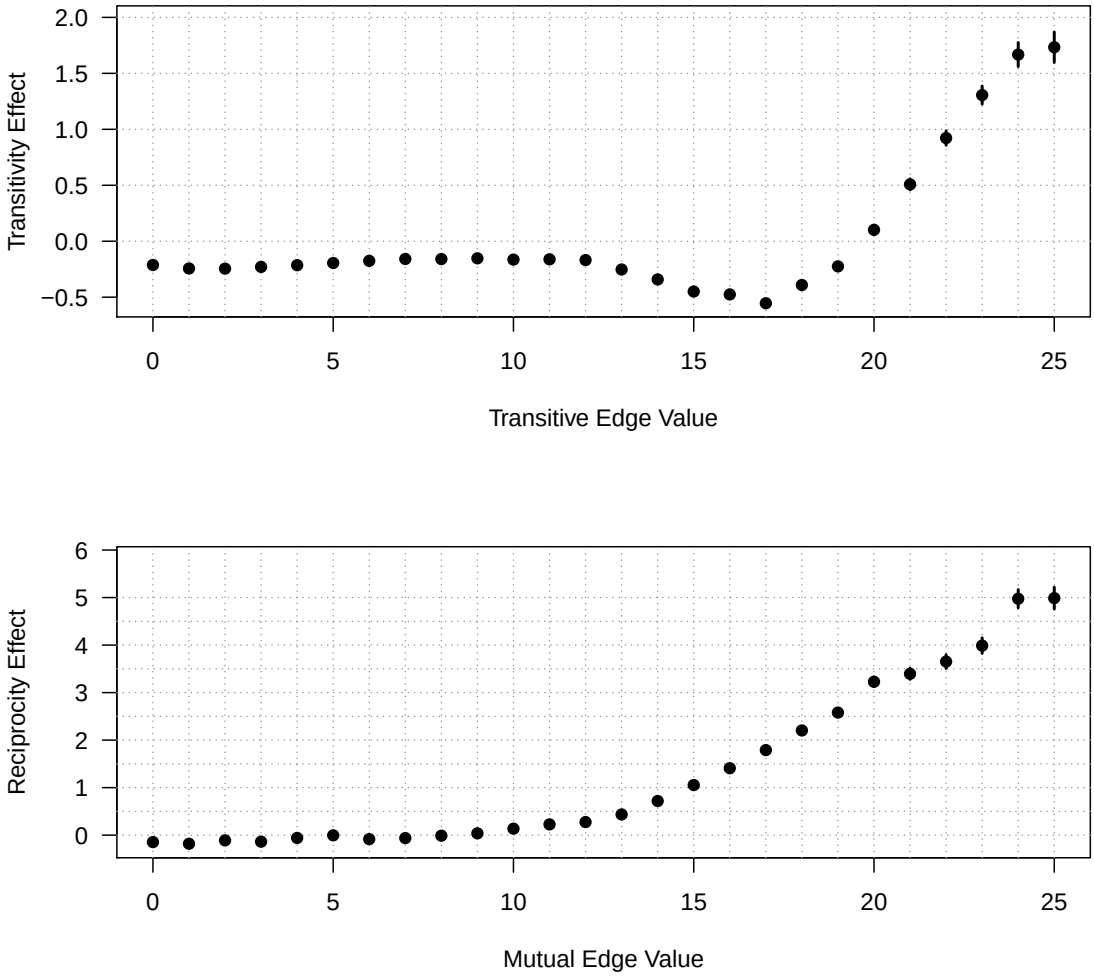

Figure 4: Plots depict the difference in predicted value (y-axis) that is attributable to the respective dependence effect, averaged over all dyads in the network. Interpretation plots are based on 1,000 FDI stock networks simulated from the 2012 model. Tie weights are measured on the natural logarithm scale. Predicted value differences are calculated by taking the differences between expected dyad values simulated from the full model with dependence terms and the null model that is based on covariates only. Error bars span 95% confidence intervals for the difference in means.

In Figure 4 we present visualizations of the effects of the dependence terms. To measure these effects we begin with a simulation exercise in which we simulate networks using both the full model with dependence terms, and the null model based only on covariates. We then classify each simulated edge value in terms of the value of the local version of the dependence

term operating on that edge. For example, when it comes to the reciprocity effect, we classify each simulated edge value ($y_{i,j}$) in terms of the value of the mutual edge, $y_{j,i}$. Finally, we estimate the difference in means between the edge values simulated from the full and null models at each dependence term value. This difference in means can be interpreted as the effect on predicted edge values of accounting for the respective dependence term in the model. The dependence effects can result in differences in predicted edge values in the range of 1–5 in log-scale FDI. The standard deviation in log-scale FDI stock (in 2012—the year we use for the interpretation plots) is 2.40. We see that the scale of both the reciprocity and transitivity effects are significant, with a shift from lower values of the relevant dependence edge to higher values resulting in more than a standard deviation increase in the predicted edge value. One other feature of these interpretation plots that is notable is the dip in the difference in means for the transitivity effect at moderate edge values. This happens because, absent the dependence effects, the independence model attributes some of the clustering in the network to exogenous covariates. The independence cannot reproduce the strong network effects observed at high edge values, but draws on the covariates to produce a modest level of clustering in the network.

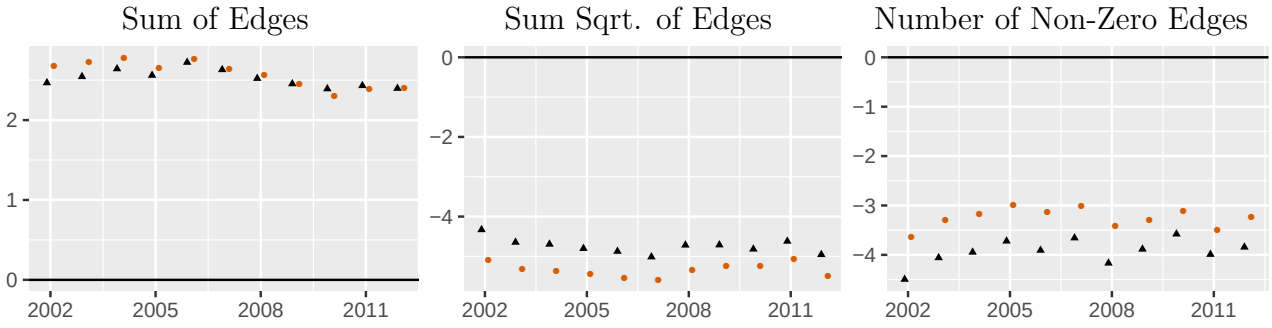

Figure 5: Estimates of network control terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity). The confidence intervals are not visible due to being small and the large range.

Network control terms, presented in Figure 5, are all significant. A positive sum of edges, the intercept term, is expected since the floor value is zero. The significant values for sum

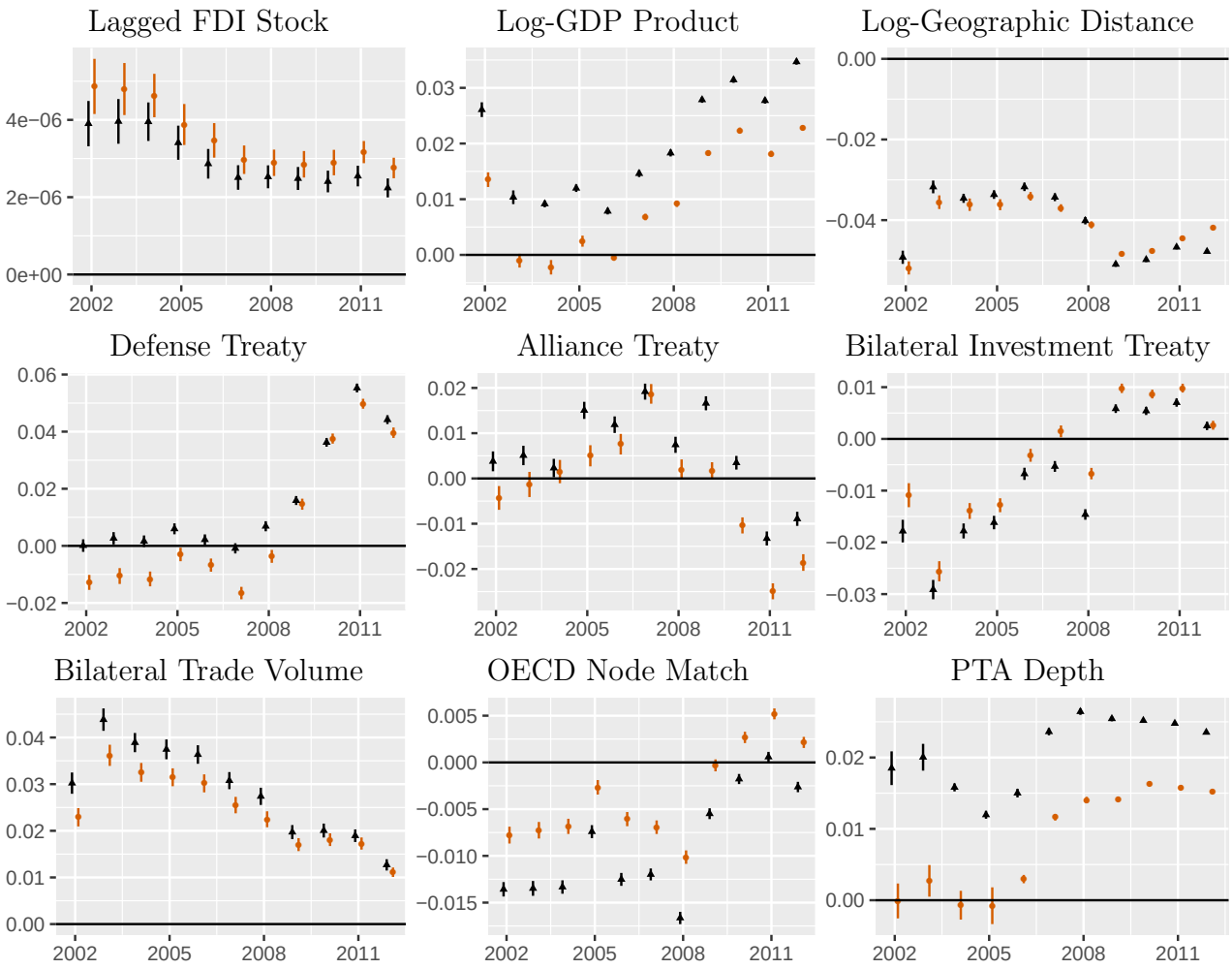

Figure 6: Estimates of exogenous edge terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity). For some models, the confidence intervals are not visible due to being small and the large range of the coefficient estimates.

square root of edges indicate the dependent variable is over-dispersed relative to a Poisson distribution and the significant values for non-zero edges show a high level of zero inflation. Regarding edge covariate determinants, presented in Figure 6, that FDI flows between a dyad are most strongly and positively correlated with bilateral trade volume and most strongly and negatively associated with distance. In addition, we see that many coefficient values are not stable over time and nearly every variable change significantly after 2007 when the Great Recession began. The shift mainly shows an increase in coefficient values for institutional agreements after the recession began. One possible explanation is that concerns about global

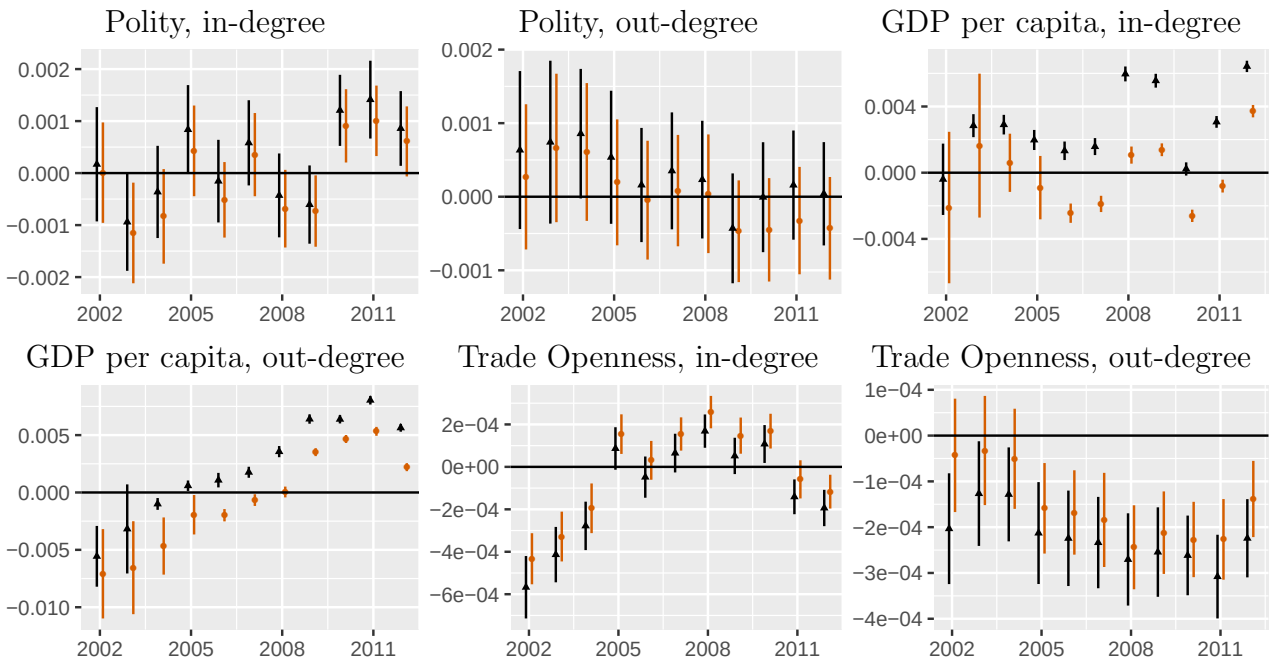

Figure 7: Estimates of exogenous node terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity). For some models, the confidence intervals are not visible due to being small and the large range of the coefficient estimates.

economic uncertainty might predominate in investment decisions at that time, so bilateral institutional relationships play a more important role.

Regarding node covariate determinants, presented in Figure 7, coefficients are often small or insignificant and even flip signs during the time sample. For example, host countries' level of democracy is not a significant predictor of inward FDI in most years except for 2010–2012. This finding is not quite consistent with the claim that democratic institutions help states to make credible commitments and thus attract FDI (e.g., Henisz, 2000; Jensen, 2003). We note three points here. First, our dependent variable is different from those in the previous research, which study net FDI inflows. Li, Owen and Mitchell's (2018) recent metaregression analysis shows that the relationship between democracy and FDI inflows is sensitive to the choice of the FDI variable (i.e., the level of net FDI inflows versus the share of net FDI inflows over GDP). Second, we model dyadic FDI while most existing studies focus on aggregate FDI inflows (monadic FDI). Third, more recent studies have shown that political institutions

have little explanatory power despite their statistical significance (Arel-Bundock, 2017*a*) and that the effect of regime type on FDI is industry specific (Wright and Zhu, 2018). Further research is needed to adjudicate the advantages and disadvantages of democratic institutions and how they matter to different investors.

We noted above that omitting dependent network structure, a condition that characterizes previous research on FDI, can result in biased estimates and improper standard errors. For several effects that we include in our models, the results are substantively changed by adding the network parameters. In general, the edge terms are more sensitive the inclusion of network terms, but node terms are still impacted. Notably, the effects of PTA depth, log-GDP product, and the homophily effect of OECD membership are consistently lower in magnitude when estimated with the network effects. The in-degree effect of GDP per capita is even estimated to be statistically significant with different signs in the independence and network models. For each of these effects, omitting the network dependencies leads an overestimate of the effect of the respective variable, a Type 2 inferential error in which the null hypothesis of no effect is incorrectly rejected, or a rejection of the null hypothesis in the incorrect direction. This finding shows that, even if a researcher is not theoretically interested in network dependencies, they should still incorporate them into an empirical model in order to avoid misspecification bias.

For the Poisson-reference ERGM these covariate estimates are usually interpreted by exponentiating Euler's constant to the power of the coefficient times the number of unit changes in the covariate to get the expected change in the tie weight (Krivitsky and Butts, 2013). Taking bilateral trade volume for example, if the FDI origin sent had a value of 10 logged units of trade, we would expect the value of logged FDI being sent to be 10.1 times more than if the trade volume was zero. Another method for interpreting covariate terms in the model is to simulate networks using the estimated coefficients while fixing all other covariate terms at the mean value and then comparing changes in the average edge value to the range of values of the covariate. For illustrative purpose, we present a plot of this

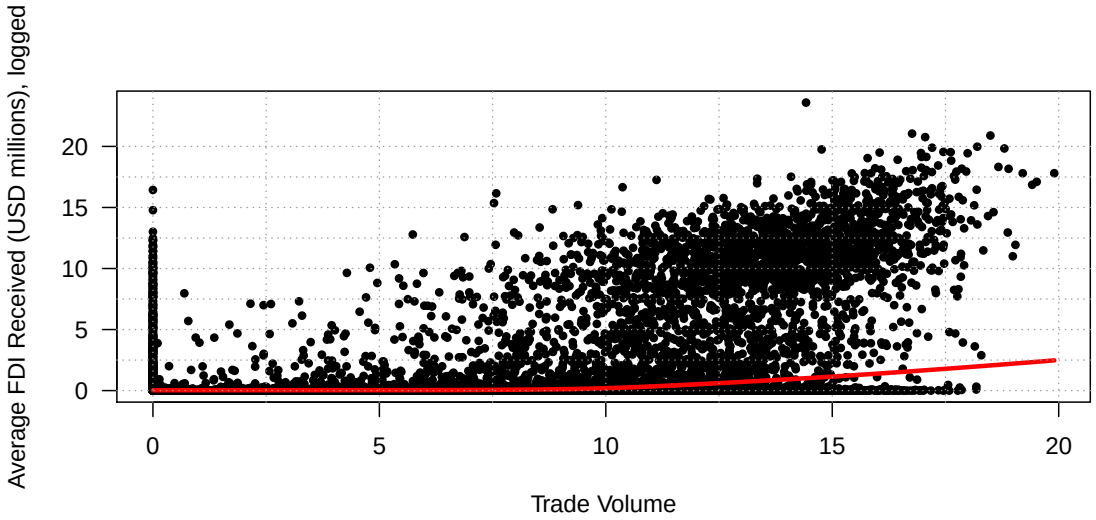

Figure 8: Results from the simulation exercise investigating the effects of bilateral trade volume for year 2012. These results are from 500 simulations. The line in red is the Loess curve.

for bilateral trade volume below in Figure 8. Here the plot shows that as the trade volume increases from zero to 10 logged units there is a slow increase in the average level of FDI received, but increases after 10 logged units show a much sharper increase.

4.1 Robustness Checks

To check the robustness of our findings, we conduct a number of different model specifications. We re-estimate the model by pooling the entire time sample (Appendix C), and use an alternative approach to address the missing data issue by subsetting to countries with more complete data (Appendix E). To assure that our results regarding transitivity and reciprocity are robust to the use of a model that can more effectively account for out-degree heterogeneity, in Appendix D we present estimates using AMEN, and find positive reciprocity and transitivity effects.

One may be concerned that bilateral investment flows can be driven by round-tripping FDI. This happens when domestic investors transfer funds to a foreign country (typically a tax haven) and invest back as "foreign capital" to take advantage of preferential policies

that their home governments offer to foreign investors (Borga, 2016). Further, firms may use tax havens to channel funds to other countries (Sauvant, 2017). If firms in one country use a tax haven to invest in another country whose firms also invest in the former country, it creates an artificial triadic closure of investment flows (i.e., transitivity). To address these concerns, we run models that exclude tax havens as well as models that control for corporate tax rate. Our main results hold the same (see Appendix F). Another concern is that FDI stock book values can be impacted by factors other than FDI flows. To partially address this, we estimate a model that includes inflation and nominal exchange rates in Appendix H.

4.2 Ripple Effects of FDI Shocks

In this section we present an analysis of how a simple shock to the FDI network—the elimination of a single edge—affects the expected values of the edges that are "close" to the eliminated edge. We investigate the interdependence in the FDI network by simulating networks from the full model estimated for 2012. Our conclusions are robust to using other years—we use 2012 for consistency with the model interpretations presented above. Our objective in this simulation experiment is to understand how the elimination of an FDI edge from country i to country j affects the other ties to which countries i and j are incident. Specifically, we analyze the effects of eliminating edge $i \rightarrow j$ on four measures: (1) the expected value of FDI ties sent by i to countries other than j, (2) the expected value of FDI ties sent by j, (3) the expected value of ties received by i, and (4) the expected value of ties received by j from countries other than i.

There are three steps in the simulation experiment we conduct to analyze the effects of eliminating edge $i \rightarrow j$. We first simulate 500 networks from the 2012 ERGM fit. We use this sample to calculate expected values of each edge, as well as our summary measures of indirect effects, from the model without constraints on edge values (i.e., no edges eliminated). Our second step is to, for each observed edge in the 2012 networks, simulate 100 networks

from the ERGM with the same parameter values, but with the respective edge value fixed to zero. Our third step is to calculate, again for each edge, the percentage change in the measures of indirect effects that result from eliminating the edge.

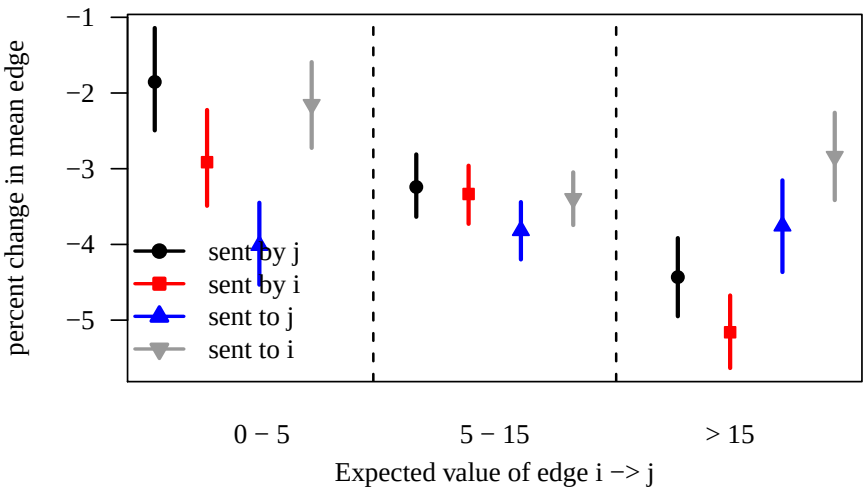

Figure 9: Results from simulation exercise investigating the effects of eliminating edge $i \to j$. Points are drawn at the average values over all edges in the 2012 network. The bars span 95% confidence intervals.

The results from our simulation exercise are presented in Figure 9. We divide the edges in the network into three categories based on their expected values—small edge values (approximately 40% of edges), between 0 and 5 on the half-log scale (i.e., $75m USD or less); medium edge values (approximately 50% of edges), between 5 and 15 on the half-log scale ($75m- $163bn USD); large edge values (approximately 10% of edges), greater than 15 on the half-log scale ($163bn USD and above). We see that the effects of eliminating an edge are uniformly negative for the surrounding edge—their expected values decrease. As the expected value of the edge being eliminated increases, the magnitude of the effects on surrounding edges increases. Even for small edge values, eliminating edge $i \to j$ from the network reduces the expected values of other edges sent to/from nodes i and j by 2-4%. When multiplied over dozens, or even hundreds, of ties to which two countries are incident, a 2-4% decrease in the value of investments would represent a substantial economic shock.

5 Conclusion

Since the 1980s, one prominent feature of globalization is that firms have increasingly unbundled and dispersed their activities across the world, leading to the expansion of complex global production networks. One central question is then what accounts for the pattern of cross-border investment flows in the age of complex interdependence. In this paper, we adopt a novel network approach to address this question. We present a network theory of FDI that includes reciprocity and transitivity as the core structural dependencies. We argue that reciprocity arises from the fact that existing MNCs serve as vehicles for information diffusion and therefore lower the transaction costs for host-country firms to invest in their home countries; Transitivity results from the expansion of global production networks and a safety net created by existing FDI linkages for investors. Empirically, we introduce the ERGM to test our hypotheses. The results of our statistical models confirm that these dependencies exist—a result that holds over time, and while adjusting for other covariates known to relate to FDI.

Our results suggest that in addition to conventional covariates such as factor endowments, market size, and institutional environments, a country's likelihood of receiving FDI depends also on its connections to existing partner states in the network. For example, a country will receive more FDI from the country that its MNCs have have already invested in and from another country when both of them have investment ties with the same third-party country. One policy implication for developing countries is that they should actively attract leading MNCs and integrate themselves into global production networks in order to attract more FDI.

We should emphasize that our theory, specification, and finding of network-wide conditional reciprocity and transitivity represent just the start in a broader scholarly dialogue on the network science of FDI flows. One limitation of our study is that we do not model any forms of conditional variation in transitivity, though we have accounted for actor heterogeneity in reciprocity. For example, if vertical FDI is the main form in triadic closures

of investment flows, we should expect transitivity to be more prevalent among groups with different factor endowments (e.g., groups with both developed and developing countries). It is thus important to explore further how network dependencies vary across different groups of countries. [20] A second limitation is that we are not able to examine the network dependencies of FDI in earlier time periods because our data covers the time period of 2001–2012 only. This is a period when countries are increasingly interconnected by complex global production networks. Therefore, network structures are important to account for FDI flows. A third limitation is that our count ERGM does not sufficiently fit the variation in FDI sender activity—a shortcoming that could be addressed through future development of specifications for count ERGMs. Finally, given the constraint of data availability, we have to rely to aggregate FDI data at the country level, though our theory is built on the logic of firm-level investment decisions. We believe it is fruitful that future research explores network dependencies at the firm level.

[20] In Appendix G, we experiment with dropping all Europe Union countries to test whether reciprocity and transitivity still hold for the rest of global economy. We find that transitivity remains highly significant and reciprocity is also largely similar to the main results, but slightly lower and less stable.

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