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

Abstract

We develop theory 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 globalization 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 flows 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 global investment flows and their political and economic consequences. In addition to our substantive findings, we offer a broad methodological contribution by introducing the ERGM for count-weighted networks in political science.

1 Introduction

What explains global 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.

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 2nd unbundling" that began in the 1980s (Baldwin, 2011). For instance, Boeing has a relationship with 5,400 supplier factories throughout the world, employing about 500,000 people through its supply chain.[1] 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 foreign 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 their connections to global production networks. For example, investments by auto makers such as Toyota, Hyundai, and Ford in India also brought in their international component suppliers (Moran, 2014, 23). If global FDI flows can arise

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

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. 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). First, reciprocity, arises from the fact that FDI represents an oligopolistic expansion strategy of MNCs and that existing MNCs help reduce the transaction costs of investing in their home country through diffusing information about their home country environments. 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. Second, the fragmentation of production processes and the expansion of global supply chains contribute to the transitivity/clustering of investment activities.

To test our arguments, we need to explicitly model interdependencies among FDI relationships between states. We introduce the the count exponential random graph model (ERGM) (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 (Cranmer and Desmarais, 2016; Desmarais and Cranmer, 2017); (2) the count ERGM is capable of modeling zero inflation in the network, which is a common 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 develop a novel network theory of foreign investment. That is, FDI flows can be shaped by structures of

interdependence—a class of generative processes that has been overlooked in the literature. 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, large consumer markets, and institutional environments, but also on its connectivity to existing partner states in the network. We believe this network approach has broad implications for understanding other cross-border economic exchanges such as aid, goods, services, and migrants, which are also likely to exhibit structural dependencies.

Second, our article adds to the growing literature on the formation of global supply chains and complex production networks. The past decades have witnessed the increasing fragmentation and globalization of production, which gives rise to complex production networks that are typically coordinated by MNCs (Baldwin, 2011; UNCTAD, 2013). Given the intertwined linkages among firms and nations, the well-functioning of the network hinges crucially on the cooperation of each involved country. Network dependencies increase the cost of governments' opportunistic behavior and thus will likely contribute to international cooperation and peace (see also Dorussen and Ward, 2010; Johns and Wellhausen, 2016; Kim and Solingen, 2017).

Third, 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; Schiavo, Reyes and Fagiolo, 2010), international lending (Gai and Kapadia, 2010; Zakaria and Fatine, 2017), overlapping capital ownership (Chuluun, 2017), and networks established through currency exchange markets (Brida, Gómez and Risso, 2009; Matesanz and Ortega, 2014). Given this growing body of evidence that economic growth and contraction spread through international economic ties, to understand what shapes domestic economies we must also understand what shapes international economic networks such as FDI. 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

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have long-run effects on the global structure of the network (see more discussions in Section 4.1.).

Finally, to our knowledge, the count ERGM has not been applied previously in political science research.[2] 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, such as interstate trade (Ward and Hoff, 2007), shared membership in international governmental organizations (Boehmke, Chyzh and Thies, 2016), the count of bills co-sponsored between legislators (Kirkland, 2013), and the number of policy ideas on which policymakers and other policy stakeholders agree (Leifeld, 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 global 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 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; Henisz, 2000; Jensen, 2003,

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[2]Although, the use of binary ERGMs has been rapidly growing in political science.

2006; Kerner, 2009; Li and Resnick, 2003; Staats and Biglaiser, 2012).[3]

One implicit assumption in existing theoretical and empirical models is that FDI flows into one country or between one dyad are independent of other countries or dyads. 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.

The primary theoretical advantage of taking a network approach to studying FDI is that we can develop and test hypotheses regarding a novel class of effects—the effects that ties in the FDI network have on each other. Through consideration of the operating characteristics of MNCs and transaction costs of investment, we derive a reciprocity hypothesis—a claim that, all else equal, investments from state i will flow disproportionately to state j if firms from state j hold a high stock of investments in state i. Through consideration of global production networks, we derive a hypothesis of transitivity—that investments from firms in state i will flow disproportionately to state j to the degree that there are third-party states k with which states i and j both exchange high investment flows.

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

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

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. In other words, the literature assumes that covariates in the model are sufficient to account for the reciprocity. 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 that FDI represents an oligopolistic expansion strategy of MNCs (Hymer, 1976; Kindleberger, 1969) and that existing MNCs diffuse information about their home country environments and thus help reduce the transaction costs of host country firms to invest in MNCs' home country. MNCs arise from exploiting their firm-specific assets to overcome imperfections in arm's-length markets (Caves, 1996; Dunning, 1992). These proprietary assets include, for example, advanced technology, brand names, product differentiation, and managerial and advertising skills, which are of a public-goods character and 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 and penetrate each other's home markets with highly differentiated products. Reciprocal FDI flows result from firms' rivalistic strategy in response to foreign entries (Graham, 1978). An MNC's successful expansion into a foreign market helps the firm better capitalize on its intangible assets and earn higher economic rents. Yet the entry also generates disruptive effects in the market, 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 into the home market of the MNC (Veugelers, 1995). 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). As a result of MNCs' rivalrous strategies, we expect FDI to flow reciprocally between pairs of countries, especially among developed countries whose firms 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,[4] which is consistent with our reciprocity argument. FDI mainly flows between pairs of developed countries, and even in the same industries, most of which is horizontal and market-seeking (Markusen, 1995, 171). Julius (1990, 22) reports that during the 1980s the percentage of FDI circulating within France, Japan, West Germany, United Kingdom, and United States (G-5) rose to 75%. Even in 2010, the figure remained high at 53%; among G-7 countries including Canada and Italy, 65% of G-7 outward FDI was absorbed by other G-7 countries.[5]

Further, MNCs act as agents of transmitting information about their home countries, which help reduce transaction costs of host country firms to invest in MNCs' home countries, thereby generating 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). This kind of information diffusion can happen via MNC's vertical linkages to their upstream suppliers and downstream customers, or more generally, through the spillover of knowledge and management know-how from MNCs to local firms. Consequently, local firms in the host country acquire more

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[4]Over the past decade, we have witnessed a surge of direct investment from emerging-market MNCs. Meanwhile, 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).

[5]Authors' calculations based on UCTAD's bilateral FDI statistics.

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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.[6] 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.

2.2 Transitivity/Clustering of FDI Flows

Transitivity, sometimes referred to as clustering, would manifest as dense triangles of FDI emerging in the FDI network. The transitivity of investment activities arise from the expansion of global production networks. One distinct feature of today's globalization is the increasing fragmentation 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 networks give rise to the clustering of FDI activities.

In a most straightforward way, MNCs' establishment of a foreign affiliate is typically followed by investment of their partners, such as upstream suppliers or downstream customers, who themselves are often multinationals that coordinate their own networks of supply chains. These types of interdependent linkages lead to multiple triangle closures of investment flows. Consider a case of three countries: A, B, and C. Suppose firms from A invest in B as suppliers to firms in B.[7] If firms in B establish foreign affiliates in C to exploit locational advantages such as a large consumer market or favorable government policies, investment by their suppliers from A likely follows to serve these foreign affiliates in C. For instance, Volkswagen's

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[6]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.

[7]Alternatively, firms in A can export intermediate goods to B. However, firms typically favor near suppliers. Moreover, if transportation and trade costs between A and B are high, firms in A will prefer direct investment over export (Carr, Markusen and Maskus, 2001).

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.[8] Airbus's establishment of its A320 assembly line in Tianjin, China has attracted 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.[9]

More importantly, global supply chains tie countries together and significantly increase the cost of governments' opportunistic behavior—such as asset expropriation or subtle policy changes. Political risk in host countries remains a primary concern of investors since footloose capital becomes an "obsolescent bargain" due to its ex post immobility (Vernon, 1971, 1980). Global production networks significantly constrain governments' policy discretion, because the proper functioning of the supply chains hinges crucially on the cooperation and coordination of the countries involved. For example, even Starbucks, a company that has a relatively simple supply chain, "sources coffee from thousands of traders, agents and contract farmers across the developing world; manufactures coffee in over 30 plants, ...; distributes the coffee to retail outlets through over 50 major central and regional warehouses and distribution centres; and operates some 17,000 retail stores in over 50 countries across the globe" (UNCTAD, 2013, 142).

When countries are integrated into MNCs' global supply chains, their governments are incentivized to refrain from arbitrary interventions or even subtle policy changes that dampen

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[8]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.

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

the supply chains. For instance, 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 and Ward (2010) demonstrate that countries are less likely to have conflicts with each other whey 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. The risk-mitigating effect of the network 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 firms in Countries A and B are linked to the foreign affiliates of MNCs from Country C 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. As a result, firms in Countries A and B are also more likely to invest in each other.

More generally, 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.

3   Data and Research Design

To test our hypotheses, we estimate a gravity model of FDI. The dependent variable is bilateral FDI stock.[10] The data are from UNCTAD, covering the time-period of 2001 to

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[10]We include a lagged dependent variable in the model such that it essentially models FDI flows. We use FDI stock 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.

2012.[11] 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.[12] The advantage of using dyadic data is that it allows us not only to model network relationships, but to measure changes in FDI inflows related to covariates that are at the dyad level, such as BITs, alliances, and bilateral trade. Following common practice, we take the natural log of the bilateral FDI stock variable.

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.[13] One challenge of using bilateral FDI data is the large number of missing values. Yet, a very large proportion of the unreported values seem likely to be zero (and thus not truly missing, but unreported because there was nothing to report). It seems that host countries are more likely to report if the value is not zero. 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, centering around zero (see Figure A in Appendix). This pattern of missingness suggests that the missing value is likely to be zero or a negligible amount. Therefore, for our main models we impute the missing values with zeros so that we have a complete data set to model network dependence. To attend to the possibility that missing values are not true zeroes due to reporting biases, we use two different methods of robustness checks. The first is that we subset our data based on the amount of missingness—limiting the network to countries for which a large proportion of the bilateral data is reported. The second is that we use multiple imputations to impute the missing values for the full data set and for the subsets based on the amount of missingness. Our main findings regarding the effects of transitivity and reciprocity remain the same when we use different approaches to address

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[11]Systematic Bilateral FDI data are not available for earlier time periods. After subsetting for available covariates we are left with 125 countries. Every year has the same countries.

[12]There are very few studies that use dyadic FDI data. See, e.g., Frenkel, Funke and Stadtmann (2004), Leblang (2010), Li and Vashchilko (2010), and Razin, Sadka and Tong (2005).

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

the missingness. Further discussion and the results of our robustness checks can be found in Appendix.

Another concern is 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 from two countries use the same tax haven to invest in each other, it creates an artificial triangle closure of investment flows (i.e., transitivity). To address these issues and check the robustness of our findings, we exclude tax havens in our data set. Our main results hold the same (see Figure H in Appendix).

3.1 Covariates

In the gravity model, we include the log product of the dyad's real GDP[14] and logged Euclidean distance.[15] Generally, higher GDP represents a larger market and therefore should be associated with more FDI, while remote 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.[16]

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 be associated with higher levels of bilateral FDI. Trade openness data are from the World

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[14]The data come from the *Penn World Table* (Feenstra, Inklaar and Timmer, 2015).

[15]See Mayer and Zignago (2011) for the calculation of Euclidean distance.

[16]The data are from the *Penn World Table*.

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., Jakobsen and De Soysa, 2006; Jensen, 2003; Li and Resnick, 2003; Li, Owen and Mitchell, Forthcoming; Resnick, 2001; Wright and Zhu, Forthcoming). We include standard polity scores as a measure of a country's level of democracy (Marshall and Jaggers, 2010). A second institutional variable included is bilateral investment treaties (BITs). This binary variable 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; Kerner, 2009).

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

3.2   Model and Specification: The Count ERGM

To model the FDI network, we must use a statistical modeling approach that is capable of representing the dependencies underlying the ties. The literature offers a number of options. These include the latent space family of models, such as those that have been used to model trade networks in political science (Ward, Ahlquist and Rozenas, 2013; Ward and Hoff, 2007); the generalized exponential random graph model (GERGM), which can be used to model complex network features in networks with continuous-valued edges (Wilson, Denny, Bhamidi, Cranmer and Desmarais, 2017); and the ERGM for count-valued edges (Krivitsky, 2012). We select the count-valued ERGM for two reasons. First, if the researcher's objective

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

is to test hypotheses regarding dependent network structure, ERGM family models can accomplish this more precisely than can latent space models (Cranmer and Desmarais, 2016; Desmarais and Cranmer, 2017). Second, the count ERGM offers a modeling advantage over the GERGM for data such as FDI flows, which are zero for the majority of dyads. That is, the count ERGM is capable of modeling zero inflation in the network. This paper presents, as far as we are aware, the first application in political science of the count ERGM proposed by Krivitsky (2012).

Like other forms of the ERGM, the count ERGM is a statistical model that operates on one or more network adjacency matrices. 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 high order network structure (i.e., network effects). If an ERGM is specified without network effects, it reduces to a dyadic regression model in which ties are assumed to be independent and identically distributed (Cranmer and Desmarais, 2011). Under Krivitsky's (2012) count ERGM, the probability of the observed $n \times n$ network adjacency matrix $\boldsymbol{y}$ is

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

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 that assures that the probabilities over all possible networks sums to one.

3.2.1 Specification

The count ERGM is extremely flexible in that there are very few constraints on the generative features that can be incorporated into the model through $\boldsymbol{g(y)}$. 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. The statistics we use to account for the individual edge distribution include,

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

which models the average edge value

$$\text{Sum, Fractional Moment} : \boldsymbol{g(y)} = \sum_{(i,j)\in\mathbb{Y}} \boldsymbol{y}_{i,j}^{1/2},$$

which accounts for dispersion in the edge distribution, and

$$\text{Non-Zero} : \boldsymbol{g}_k = \sum_{(i,j)\in\mathbb{Y}} \mathbb{I}(\boldsymbol{y}_{i,j} \neq 0),$$

which models the prevalence of zeros in dyadic FDI flows. 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. Second,

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

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which acounts 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) triangle. 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. These two variants of node-level statistics differentiate between the effects of a variable on the volume of FDI originating from a state, and being invested in a state, respectively.

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

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

The count ERGM estimates that we present below are estimated using the `ergm` (Handcock, Hunter, Butts, Goodreau, Krivitsky and Morris, 2017) and `ergm.count` (Krivitsky, 2016) packages in the `R` statistical software (R Core Team, 2015). 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., Cao and Ward, 2014; Cranmer, Desmarais and Kirkland, 2012; Cranmer, Heinrich and Desmarais, 2014; Ward and Hoff, 2007). By allowing the parameters to change with each year, we can observe the temporal robustness of effects, and avoid imposing the limiting assumption that the coefficient values are stable. Indeed, 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. Since the conventional approach in the study of FDI is to pool time periods into a panel, we present pooled results in Section B in Appendix.

4   Results

Before discussing individual effects, we first assess the relative fit of the independence and network models. Figure 1 presents the difference in Bayesian Information Criterion (BIC) in the between the independence and network models for each year in our analysis. The BIC is more conservative in terms of adding parameters to a model than the common alternative likelihood-based measure of model fit, the Akaike Information Criterion (AIC) (Raftery, 1999; Waldorp, Huizenga, Nehorai, Grasman and Molenaar, 2005). 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.

To illustrate how the network model fits better, we compare the fit of the two models to the level of reciprocity in the FDI ties. The level of reciprocity is defined as

$$\frac{\sum_{(i>j)} \mathbf{1}\left(\boldsymbol{y}_{i,j} > 0 \cap \boldsymbol{y}_{j,i} > 0\right)}{\sum_{(i>j)} \mathbf{1}\left(\boldsymbol{y}_{i,j} > 0 \cup \boldsymbol{y}_{j,i} > 0\right)}.$$
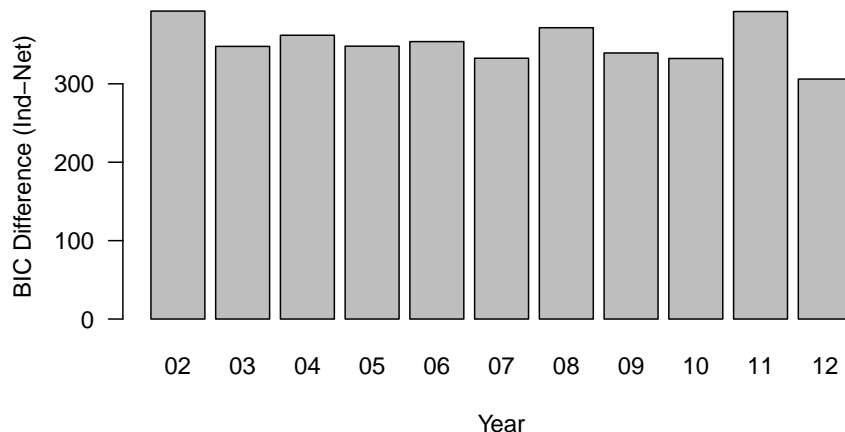
Figure 1: Difference in BIC between independent and network model.

In other words, this is the proportion of dyads in which there is an FDI tie from state i to state j and a tie from state j to state i out of the number of dyads in which there is at least one tie. This measures the degree to which the presence of a tie in one direction within a dyad implies that the other tie will exist. To compare the network and independent models we simulated 1,000 networks from each, and compare the reciprocity values in the simulated networks to the observed reciprocity value. We see in Figure 2 that the network model provides a much better fit to the observed level of reciprocity (approximately 0.32) than the independent model. Indeed, the observed value is an extreme outlier with respect to the distribution of reciprocity values of networks simulated from the independent model. Unlike the BIC, the fit to the observed reciprocity value does not provide a holistic assessment of model fit. Rather, it illustrates the improved regarding an interpretable quantity in the FDI network, and illustrates how a model in which independence is assumed provides a relatively poor fit to this quantity.

Turning now to the network effects, which are presented in Figure 3, we see that the reciprocity and transitivity effects are positive and statistically significant in each year, offering robust evidence that FDI flows are interdependent according to these two canonical forms of
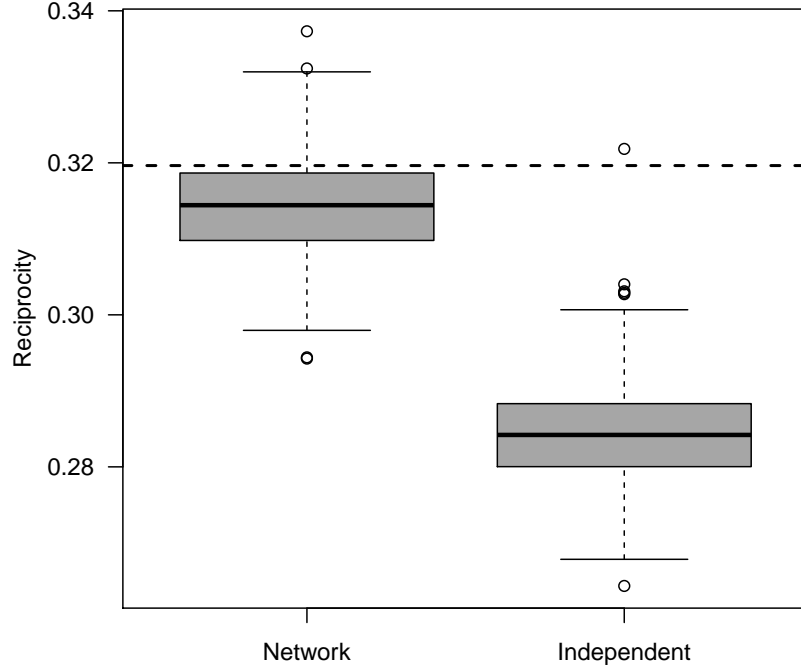
18

Figure 2: Reciprocity values of 1,000 networks simulated from the Network and Independent models. Observed value given by the dashed horizontal line.

network structure.[18] The dependence effects, though formulated intuitively, do not permit a straightforward marginal-effects interpretation of the coefficients aside from the signs of the effects. We can, however, estimate and visualize the dependence effects using simulation. 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

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[18]As noted in the Section 3, we also tested our hypotheses on different subsets using different methods of imputation. The majority of these results support our hypotheses, although in the smaller subsets reciprocity is not significant for every year estimated. When subsetting based on missingness, we are only left with more developed countries. This indicates that reciprocity might be conditional on the relative level of development between dyads.
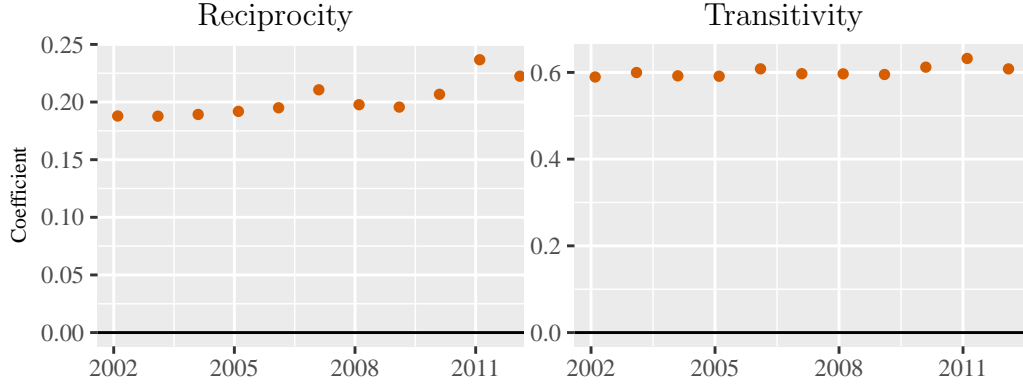
Figure 3: Estimates of Network terms in Poisson ERGMs. Bars span 95% confidence intervals.

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.

We see in Figure 4, that the dependence effects can result in differences in predicted edge values in the range of 1–4 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.
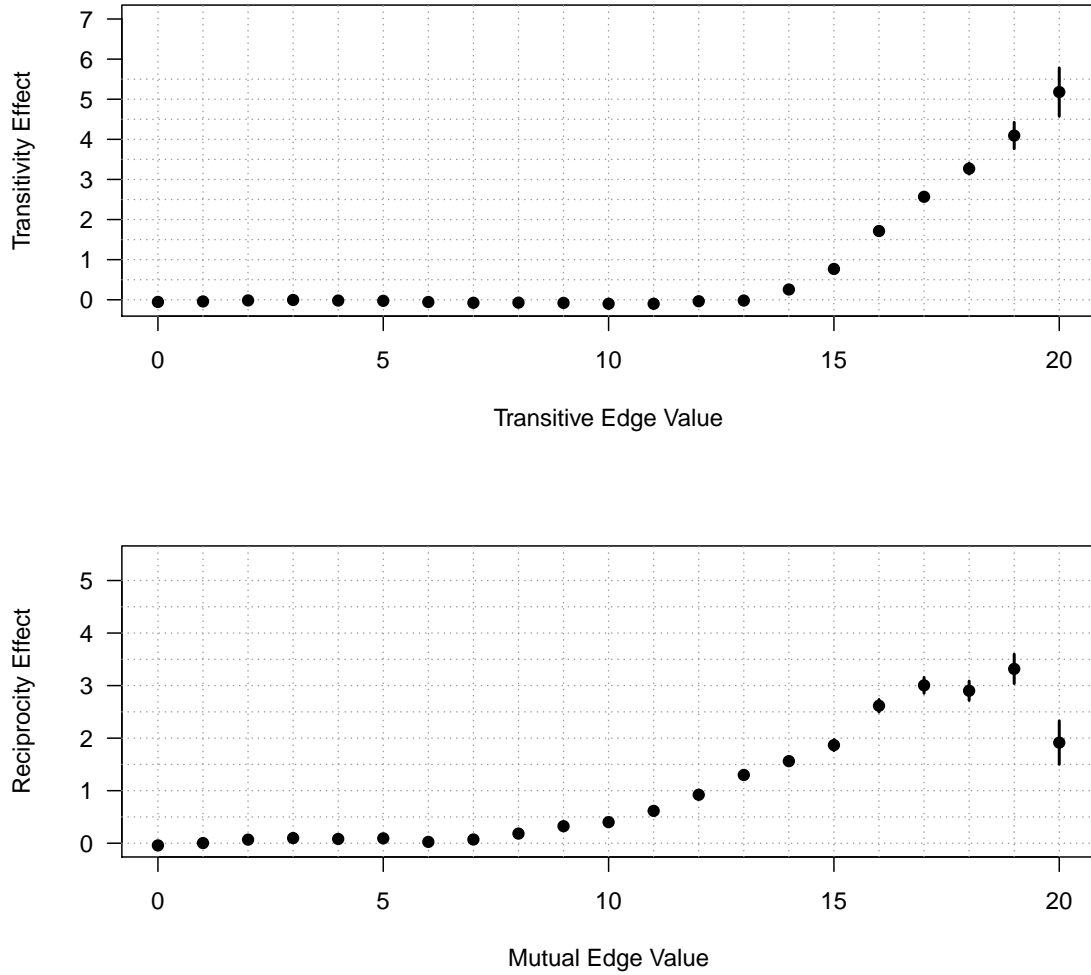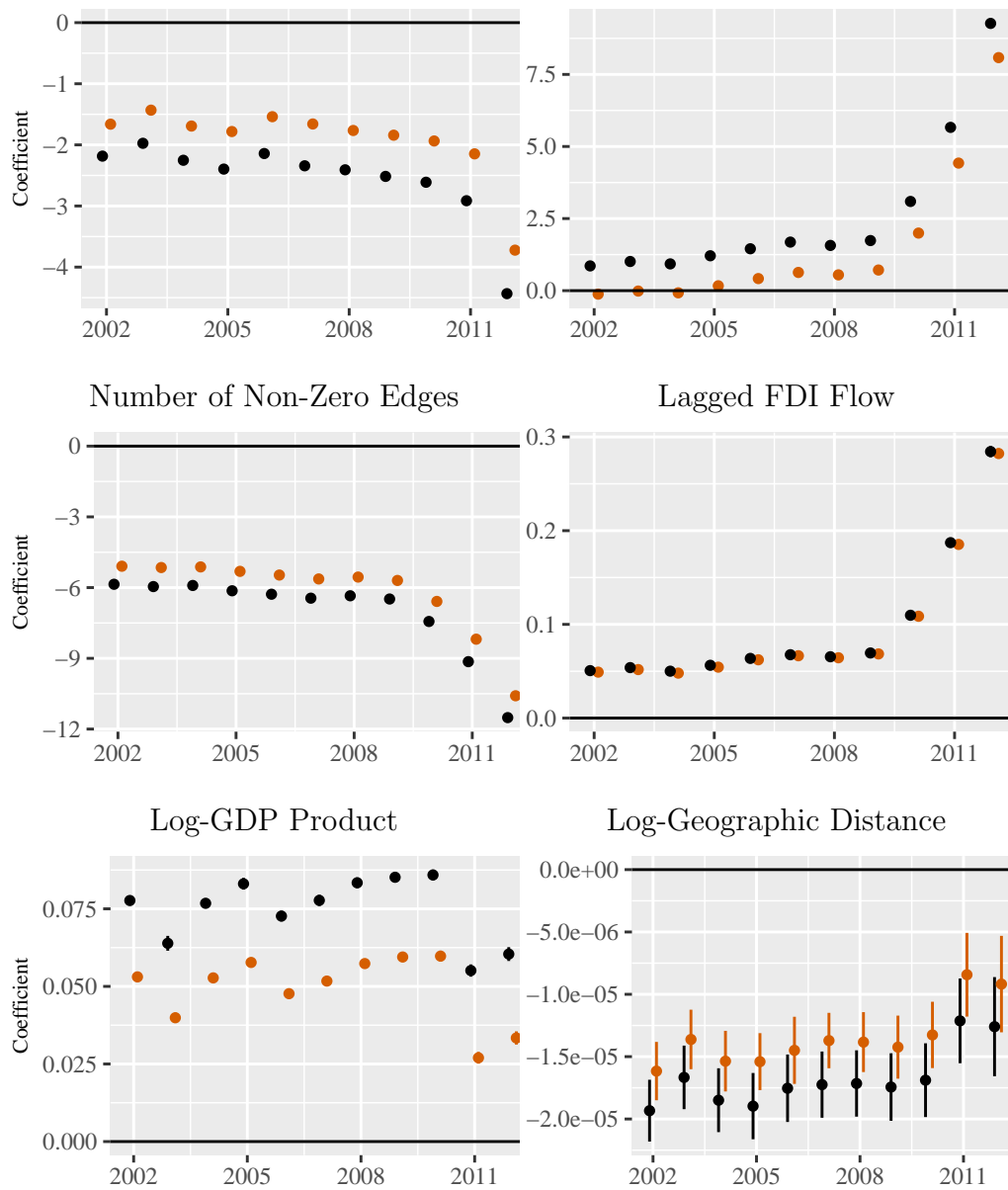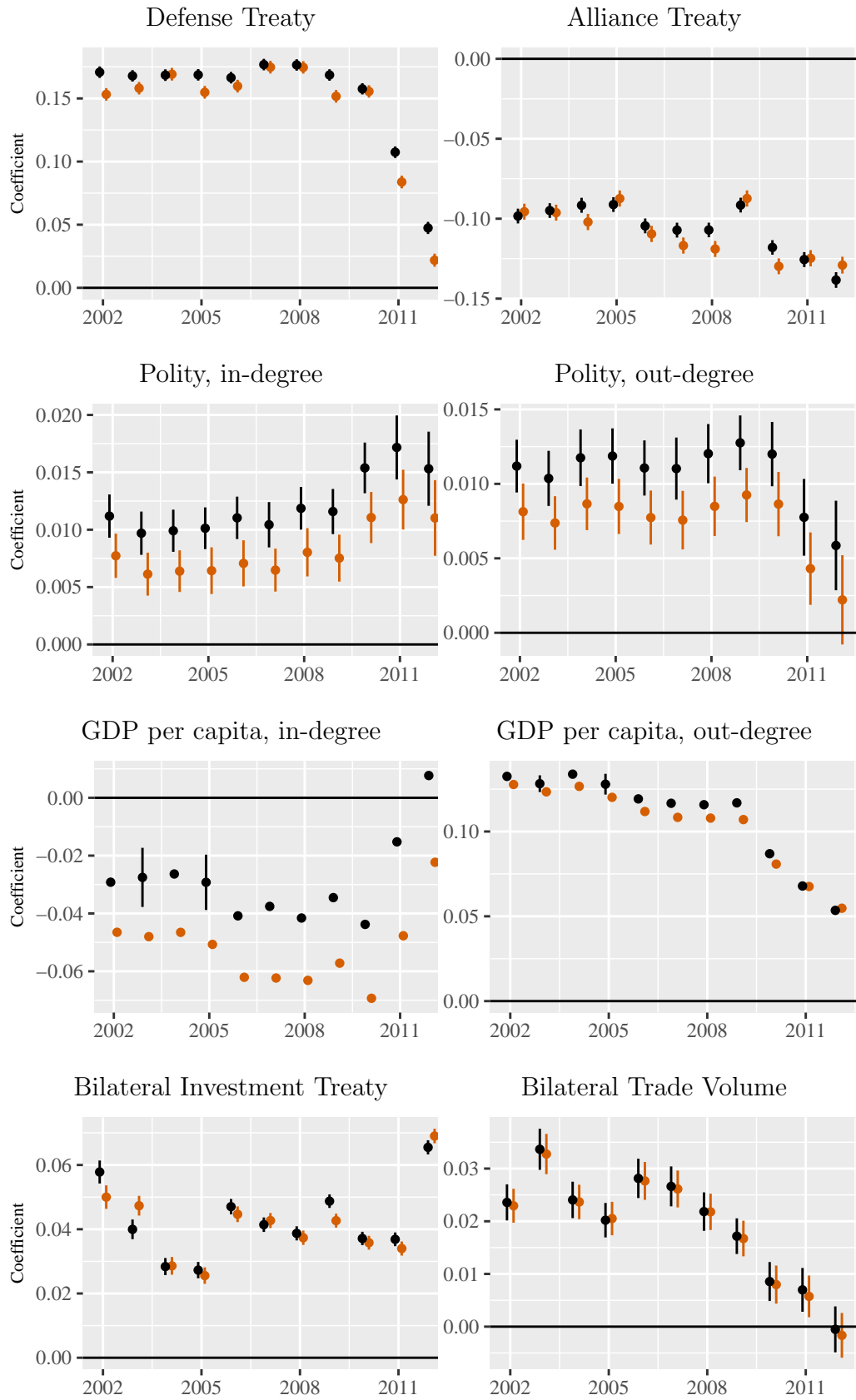
Figure 4: Plots depict the difference in predicted value (y-axis) that is attributable to the respective dependence effect, averaged over all dyads in the network. Interpretation plots are based on 1,000 FDI stock networks simulated from the 2012 model. Tie weights are measured on the natural logarithm 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.

Sum of Edges   Sum Sqrt. of Edges

Number of Non-Zero Edges

Lagged FDI Flow

Log-GDP Product

Log-Geographic Distance

Defense Treaty

Alliance Treaty

Polity, in-degree

Polity, out-degree

GDP per capita, in-degree

GDP per capita, out-degree

Bilateral Investment Treaty
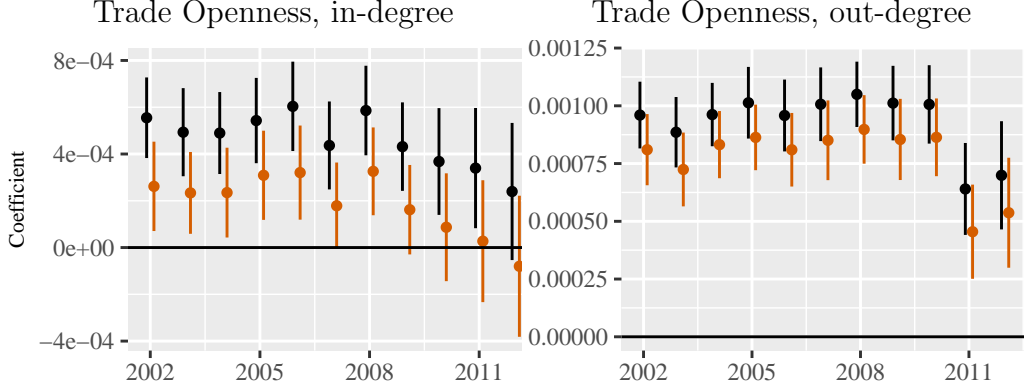
Bilateral Trade Volume

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Table 1: Estimates of exogenous terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).

Regarding covariate determinants, presented in Table 1, the results show that FDI flows between a dyad are strongly and positively correlated with the product of the dyad's GDP, BIT, defense treaty, both destination and origin countries' polity scores and trade openness, and origin country's GDP per capita. On the other hand, FDI flows are negatively associated with geographic distance between a dyad, alliance treaty, and destination country's GDP per capita. In addition, we see that the coefficient values are not stable over time. Several parameters such as geographic distance, defense treaty, as well as origin and destination's polity scores, GDP per capita, and trade openness change significantly after 2008 when the Great Recession began. The magnitude of most of these coefficients decreases since then. One possible explanation is that concerns about global economic uncertainty might predominate in investment decisions at that time so that home and host countries' political and economic characteristics play a less important role.

We noted above that omitting dependent network structure, a condition that character- izes 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 the network model, we find the following effects to be lower in magnitude, statistically significant in fewer years, or both: Gravity model mass,

distance, destination polity, destination trade openness, origin trade openness, origin GDP per capita, origin polity, and origin trade openness. For each of these effects, our results indicate that omitting the network dependencies lead to either an overestimate of the effect of the respective variable, or worse, a Type 2 inferential error in which the null hypothesis of no effect is incorrectly rejected. This finding shows that, even if a researcher is not theoretically interested in network dependencies, (s)he should still incorporate them into an empirical model in order to avoid misspecification bias.
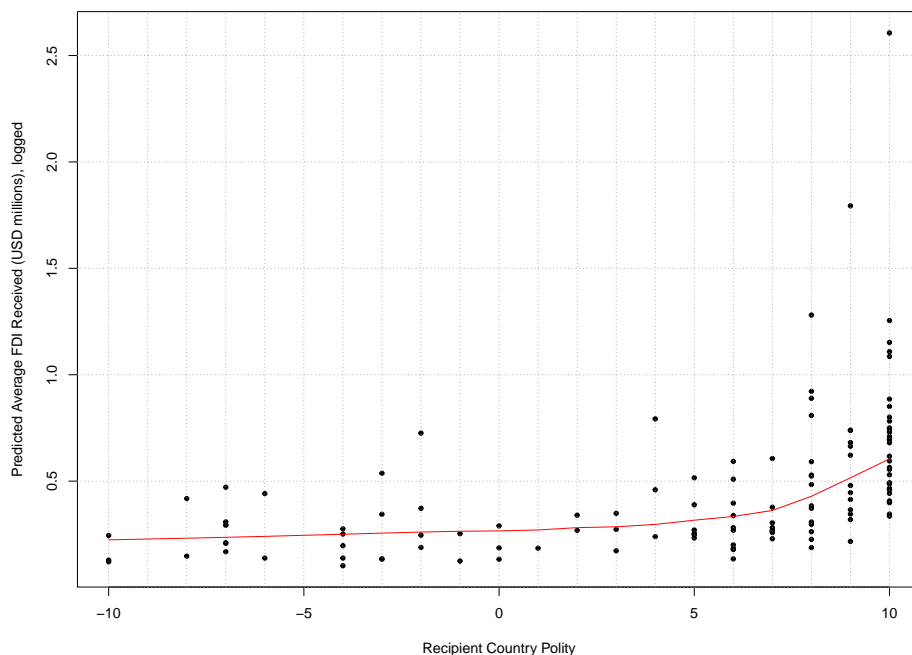

Figure 5: Results from the simulation exercise investigating the effects of Polity, in-degree for year 2002. The points are calculated as the the receiver node averages in the adjacency matrix. These results are from 500 simulations. The line in red is the Loess curve.

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 Polity, in-degree for example, if the FDI destination had a Polity score of 10 in 2002, we would expect the value of logged FDI being sent to be 1.27 times more than a destination that had a Polity score of -10. In the model with network terms this

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expected increase is only 1.17 times higher. Another method for interpreting independent terms in the model is to simulate networks using the estimated coefficients while fixing all other independent terms at the mean value and then comparing changes in the average edge value to the range of values of the covariate. For node-level covariates the method is similar. The only change is that you use the column (receiver) averages in the adjacency matrix to compare against covariate values. For illustrative purpose, we present a plot of this for Polity, in-degree below in Figure 5. Here the plot shows that as the destination state's Polity increases from the score -10 to the score of 6 there is a slow increase in the average level of FDI received, with a sharper increase between Polity Scores 7 and 10.

4.1 Ripple Effects of FDI Shocks

One of the central advantages of the network perspective is that it sheds light on the interdependence in the system. As we reviewed above, economic contagion has been largely theorized as the ways in which country-level economic conditions can spread through the edges in an economic network. Our analysis reflects a different form of interdependence— characterizing the ways in which the edges in the network depend upon each other. The ERGM provides a framework for investigating the patterns of dependence among edges in order to understand how edges in the network depend upon each other. 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. The complete elimination of a single FDI edge would be admittedly rare, but the effects would be similar to that of a large reduction in an edge value and simulating the network conditional on a fixed but non-zero edge value is much more computationally complex than eliminating an edge entirely. Another way to look at edge elimination is to consider the structural differences we would have observed if a policy was in place to prevent investment along a particular edge (e.g., via an embargo on investment). This exercise contributes to our understanding of contagion and domino effects in the international economic system.

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 $i \to j$ 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. These edges are "close" to edge $i \to j$ according to our ERGM specification in that (1) the edge sent from j to i factors directly into the measure of reciprocity, and (2) all edges sent to (from) i and j by other nodes factor into the transitive triads measure with the edge from i to j.

There are three steps in the simulation experiment we conduct to analyze the effects of eliminating edge $i \to j$. 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.

The results from our simulation exercise are presented in Figure 6. 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 log scale (i.e., $150m USD or less); medium edge values (approximately 50% of edges), between 5 and 10 on the log scale ($150m- $22bn USD); large edge values (approximately 10% of edges), greater than 10 on the log scale ($22bn USD and above). We see that the effects of eliminating small and medium sized edges are mixed. The adverse effects are confined to the sending country i itself. This result
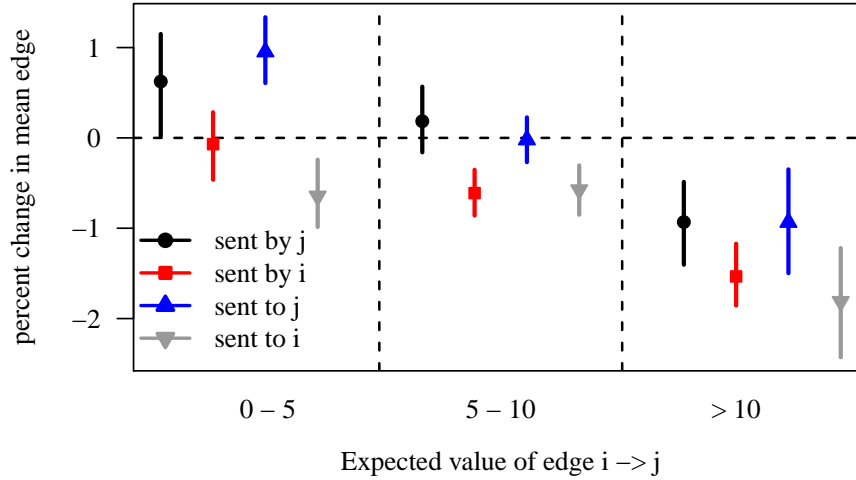
Figure 6: Results from simulation exercise investigating the effects of eliminating edge $i \rightarrow j$ on the expected values of other edges incident to both i and j. Points are drawn at the average values over all edges in the 2012 network. The bars span 95% nonparametric bootstrap confidence intervals, which are constructed by resampling edges. Expected values of edges are expressed on the natural logarithm scale.

could be attributable to the inability to detect domino effects of a relatively small perturbation to the network—the elimination of a single edge—when the edge's value is small. However, as the expected value of the edge being eliminated increases, a consistent signal emerges. For large edges, eliminating edge $i \rightarrow j$ from the network reduces the expected values of other edges sent to/from nodes i and j by 1-2%. When multiplied over dozens, or even hundreds, of ties to which two countries are incident, a 1-2% decrease in the value of investments would represent a substantial economic shock. For example, a economic crisis in countries at the center of the network, such as the U.S., will have a ripple effect on FDI inflows and outflows in many other countries with which the U.S. even doesn't have a direct investment tie. Therefore, the cost of any disruption to the network is multiplied by the interdependence. This simulation exercise illustrates the consequences of interdependence in FDI networks.

5 Conclusion

Since the 1980s, one prominent feature of the global economy is the growth of global production networks. Firms have chosen to invest overseas at an unprecedented level, and consequently, production is increasingly fragmented and organized across the globe. One central question is then what accounts for the pattern of global investment flows. In this paper, we adopt a novel network approach to address this question. FDI flows represent ties between states that arise through both a complex underlying network of inter and intra-firm relations, and legal agreements between states. The relational backdrop through which FDI operates leads to predictable network structure in the patterns of ties formed through FDI. We present a network theory of FDI that includes reciprocity and transitivity as the core structural dependencies. 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.

We should emphasize that our theory, specification, and finding of network-wide 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 reciprocity and transitivity. In theory, we should expect that the degree of reciprocity varies by countries' levels of development. 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; Melitz, 2003). Historically, MNCs from developed countries predominate. Although there is a surge of FDI from developing countries since the early 2000s, firms in most developing countries are still not competitive enough to strive in a global market.[19] It is important to

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[19]For instance, in 2005 outward FDI flows and stocks from developing countries are approximately 17% and 13% of the world total, respectively (UNCTAD, 2006). Furthermore, outward FDI from developing countries is highly concentrated; the top 10 countries, mostly large emerging economies such as Argentina, Brazil, Chile, China, Mexico, Russia, and South Africa contribute about 83% (UNCTAD, 2006).

explore how network dependencies vary across different groups of countries.

Future research could also look into the political and economic consequences of FDI networks. In this article, we take a first step to model the characteristics of FDI networks and show that they exhibit both reciprocity and transitivity. The methodological advancement now allows researchers to examine the effects of the global structure of the network on states. Given the dramatic expansion of global production networks and states are increasingly tied to each other through multinationals' investment activities, it is pivotal to understand the consequences of FDI networks, such as how the networks transmit exogenous shocks, influence domestic politics, and shape international cooperation and conflict.

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