The Network of Foreign Direct Investment Flows: Theory and Empirical Analysis

Abstract

We study the structure of the international network of foreign direct investment (FDI), which has been overlooked in extant literature. We develop a novel network theory and argue that FDI flows are reciprocal and transitive. Empirically, we integrate hypotheses regarding exogenous covariate determinants and structural network dependencies into an exponential random graph model for weighted networks. Our empirical results show that FDI networks exhibit both reciprocity and transitivity. Our article takes a first step to study FDI networks and provides new insights that FDI flows can arise from the interdependences of the outcome variable. It thus supplements existing theories of FDI that focus exclusively on the explanatory power of covariates. Our findings have important implications for understanding global production networks 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 (148 words).

1 Introduction

What accounts for the patterns of 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 proprietary 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 (UNCTAD, 2013, xxi). This is referred to as the "globalization's 2^{nd} unbundling," which tends to exhibit regional clustering (Baldwin, 2011). For instance, 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 can no longer be understood simply as a result of individual firms' decisions to exploit their 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 endogenously from the network structure, conventional political economy models of FDI remain *incomplete* by excluding high-order structural variables.

We argue that two network structures—reciprocity and transitivity—are important to account for the pattern of cross-border FDI flows. First, reciprocity arises from the fact that FDI represents an oligopolistic expansion strategy of MNCs and that MNCs, through diffusing information about their home country environments, help to reduces the transaction costs of investing in their home country. 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 to country i. Second, the fragmentation of production processes and the expansion of global supply chains contribute to the transitivity/clustering of investment activities. This pattern is further enhanced by the diffusion of preferential trade agreements (PTAs) that allow MNCs to optimize their supply chains within member states to better exploit location advantages such as factor endowments and favorable government policies.

To test our arguments, we need to explicitly model interdependencies of the outcome variable. Yet, conventional covariate-based modeling approaches typically assume that countries and dyads are independent of each other. In the paper, we introduce the the count exponential random graph model (ERGM), which is developed by Krivitsky (2012). The count ERGM is suitable for testing our argument for two reasons: (1) ERGM family models allow us to test hypotheses regarding dependent network structure more precisely than latent space models (Cranmer and Desmarais, 2016; Cranmer, Leifeld, McClurg and Rolfe, 2016; Desmarais and Cranmer, 2017); the count ERGM is capable of modeling zero inflation in the network, which is a common characteristic of bilateral FDI data. Utilizing bilateral FDI flow data from the United Nations Conference on Trade and Development (UNCTAD) over the period of 2001–2012, 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.

Our article makes 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. In conventional theories of FDI, firm-level characteristics and country-level political and economic parameters account for cross-border investment flows. We argue and empirically show that FDI flows can arise from its network interdependencies. 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. Our network approach therefore supplements existing theories and offers new insights into understanding the pattern of global direct investment.

We believe this network approach has broad implications for understanding other cross-border movements of aid, goods, services, people, etc., which are central themes in the International Political Economy literature. Global international trade regimes, for instance, are explicitly designed based on the principle of reciprocity (Bagwell and Staiger, 1999). Yet empirical studies of trade flows rarely account for the pattern of reciprocity. Likewise, we expect other global economic exchanges to exhibit structural characteristics as well.

Second, our article adds to the growing literature on the formation of global supply chains and complex production networks and their political and economic consequences. 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 (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. Countries' embeddedness in the network increases the cost of governments' opportunistic behavior that disrupts the network. Hence, network dependencies will likely contribute to governments' cooperative behavior (see also Johns and Wellhausen, 2016) and promote international cooperation and peace (see also Dorussen and Ward, 2008, 2010; Kim and Solingen, 2017).

Further, understanding interdependence through FDI networks is critical to understanding the global economic system as a whole. Countries are linked through economic ties. 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; Lagunoff and Schreft, 2001; Leitner, 2005; 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 have long-run effects on the global structure of the network (see more discussions in Section 4.1.).

Finally, to our knowledge, this recent extension of ERGM has not yet been applied in political science research. Our use and introduction of the count ERGM represents two distinct contributions. First, the application of the count ERGM to the study of bilateral FDI results in novel findings regarding patterns of dependence that characterize the FDI network. Second, by introducing the count ERGM in political science, we provide an illustrative application of a methodology that is widely applicable 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 (or ties that can reasonably be converted to counts), 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 network should be characterized by 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-level characteristics and country- and 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 vulnerable to government expropriation (Vernon, 1971, 1980). This literature focuses on role of domestic and international institutions in preventing state's predatory behavior and ensuring credible commitment, thereby attracting FDI (e.g., Allee and Peinhardt, 2011; Büthe and Milner, 2008; Henisz, 2000; Jensen, 2003, 2006; Kerner, 2009; Li and Resnick, 2003; Staats and Biglaiser, 2012).

There is now a profuse empirical literature examining the economic, political, and institutional determinants of FDI inflows.[1] Existing studies typically model FDI flows at the monadic and to a lesser extent at the dyadic level. 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 (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 tie in the FDI network have on each other. In deriving our theoretical claims regarding network dependence, we focus on the operating characteristics of MNCs, transaction costs of investment, and global production networks, which are central to the FDI process. Through consideration of the structure and function of MNCs, we derive a reciprocity (Garlaschelli

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

and Loffredo, 2004) 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 (Holland and Leinhardt, 1971)—that investments from firms in state i will flow disproportionately to state j to the degree that there are third-party states k in 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 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. But, it 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 environment and thus help to reduce the transaction costs of host country firms to in their 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, generating reciprocal flows of investment. For example, reciprocal FDI flows can result from firms' rivalistic strategy in response to foreign entries (Graham, 1978): foreign entry generates disruptive effects in the market, which stimulates rivalrous expansion of local firms into the home market of the foreign firm.[2]

Historically, global investment activities have been dominated by MNCs from developed countries and characterized by a pattern of two-way flows.[3] 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.[4]

Further, MNCs act as agents of transmitting information about their home countries, which help reduce transaction costs of host country firms to invest in their home countries, thereby generating reciprocal flows of investment. Investing in a foreign country incurs a

[2]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).

[3]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).

[4]Authors' calculations based on the UCTAD bilateral FDI statistics.

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 to 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. As a consequence, 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 the MNCs' home country. 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.

Recently, governments have increasingly used the principle of reciprocity to regulate FDI flows, which further reinforces the reciprocity of FDI. In order to gain access to foreign markets, MNCs have incentives to leverage their influence on home governments to exchange market accesses with foreign governments. As Crystal (2003, 6) note, "[MNCs] want to counter the existing restrictions—on both trade and FDI—that some foreign countries have imposed and so therefore will favor contingently restrictive policies." Both governments and citizens have a tendency to react to inward foreign investment following a principle of reciprocity. Tingley, Xu, Chilton and Milner (2015) show that U.S. government officials are more likely to oppose Chinese firms' mergers and acquisitions when China has blocked U.S. investment. Likewise, the India government is to propose a reciprocity-based policy towards foreign investment. Piyush Goyal, the Minister of State Power, Coal, Renewable Energy, and Mines, said in an interview, "India won't allow power companies to invest from countries where Indian firms are banned."[5] With regard to mass support for FDI, experimental evidence shows that citizens are more likely to favor foreign investment from countries that grant reciprocal market access (Chilton, Milner and Tingley, Forthcoming). In this regard, reciprocity ameliorates the concern about MNCs' legitimacy in host countries. Therefore, we hypothesize the following:

Hypothesis 1: FDI flows are reciprocal.

2.2 Transitivity/Clustering of FDI Flows

Transitivity, sometimes referred to as clustering, is the tendency for a node (i.e., state) to form ties with friends of friends—other nodes tied to their existing neighbors in the network (Holland and Leinhardt, 1971). The transitivity of investment activities arise from the expansion of global production networks and is further reinforced by the diffusion of PTAs. One distinct feature of today's globalization is the increasing fragmentation of production processes and the dramatic expansion of global supply chains (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 purchasers, 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.[6] If firms in B establish foreign affiliates in C to exploit locational advantages

[5] Singh, Sarita. "India to Give a 'Power' Blow to Chinese Firms Soon." *The Economic Times*, May 22, 2017. `http://economictimes.indiatimes.com/industry/energy/power/security-concerns-indias-new-rules-to-bar-chinese-companies-in-power-sector/articleshow/58780085.cms`, Accessed June 6, 2017.

[6] Alternatively, firms in A can export intermediate goods to B. However, firms typically favor near sup-

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 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.[7]

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).

Governments are incentivized to refrain from arbitrary interventions or even subtle policy changes that dampen firms' profitability levels. Especially when two countries are integrated into the same global production network coordinated by leading MNCs in a third country,

pliers. 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).

[7]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.

the risk-mitigating effect of the network is magnified. This is because all countries involved have strong incentives to ensure the well functioning of the network. 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. Therefore, we expect that FDI has a high probability to flow among countries that are in the same global production network, resulting in the transitivity/clustering of investment activities.[8]

In addition, the diffusion of PTAs is likely to further enhance the clustering of direct investment activities. The formation of a PTA eliminates trade barriers among member states. The removal of trade barriers allows MNCs to fragment its production stages within member states and optimize their global supply chains to best capitalize on locational advantages such as factor endowments and favorable government policies. For instance, with the increasing integration of the European Community, the 1980s witnessed a restructuring of many industries and regionalization of MNC activities to exploit the advantages of a single market, leading to a surge of intra-region FDI (UNCTAD, 1991, 34). Importantly, most favored-nation treatment, investment clauses, and dispute-settle mechanisms that are embedded in PTAs help to alleviate foreign investors' concerns about government interventions, discrimination, and expropriation (Büthe and Milner, 2008; Büthe and Milner, 2014), thereby making member states more attractive investment destinations to each other. Note that the clustering of MNC activities can proceed the formation of a PTA. For example, investments were already clustering among Canada, Mexico, and the United States before the signing of the North American Free Trade Agreement. Our point is that PTAs engender

[8]In a broader term, 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.

opportunities for MNCs to reorganize their activities within member states to better utilize their firm-specific assets and exploit local advantages, hence reinforcing the transitive clustering of investment activities. Therefore, we hypothesize that:

Hypothesis 2: FDI flows are transitive.

3 Data and Research Design

To test our hypotheses, we estimate a gravity model of FDI.[9] The dependent variable is bilateral FDI stock.[10] The data are from UNCTAD, covering the time-period of 2001 to 2012. The data set was first made available in 2014 (UNCTAD, 2014).[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.

3.1 Missingness

Bilateral stock levels are self-reported and only reported if the value is not zero for all years. Because of this, around 83% of the dyadic values are missing. The missingness is strong evidence that the value should be zero or is a negligible amount and for our main models we impute zeros. Comparing world totals to bilateral totals, we find that the difference is

[9] We follow as closely as possible the model specification in Li and Vashchilko (2010).

[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.

[11] Systematic Bilateral FDI data are not available for earlier time periods.

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

small. A density plot can be found in Appendix A with the summary statistics. 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. The second is that we use multiple imputations to impute the missing values for the full dataset and for the subsets based on the amount of missingness. Further discussion and results can be found in Appendix C and D.

3.2 Covariates

In the gravity model, we include the log product of the dyad's real GDP[13] and logged Euclidean distance.[14] 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.[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 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., Jakobsen and De Soysa, 2006; Jensen, 2003; Li and Resnick, 2003; Li, Owen and Mitchell, 2016; Resnick, 2001). We include standard polity scores as a measure of a country's level of

[13]The data come from the *Penn World Table* (Feenstra, Inklaar and Timmer, 2015).
[14]See Mayer and Zignago (2011) for the calculation of Euclidean distance.
[15]The data are from the *Penn World Table*.

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 (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).[16]

3.3 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 (Desmarais and Cranmer, 2012; 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 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; Cranmer et al., 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

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

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.

3.3.1 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 $\boldsymbol{g}(\boldsymbol{y})$. 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,

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

which models the average edge value

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

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,

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

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,

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

which 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 flows that the node sends. The second, "Receiver Covariate," uses the sum over the flows 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.

$$\text{Sender Covariate} : \boldsymbol{g(y, x)} = \sum_i x_i \sum_j \boldsymbol{y}_{i,j}$$

$$\text{Receiver Covariate} : \boldsymbol{g(y, x)} = \sum_j x_j \sum_i \boldsymbol{y}_{i,j}$$

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 the 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) (Abrahamowicz and Ciampi, 1990; 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.

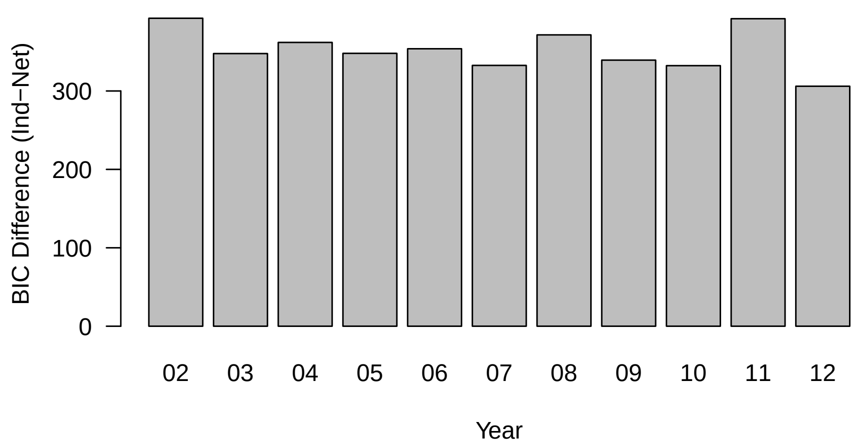


Figure 1: Difference in BIC between independent and network model.

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

$$\frac{\sum_{(i>j)} \mathbf{1}\left(\boldsymbol{y}_{i,j} > 0 \cap \boldsymbol{y}_{j,i} > 0\right)}{\sum_{(i>j)} \mathbf{1}\left(\boldsymbol{y}_{i,j} > 0 \cup \boldsymbol{y}_{j,i} > 0\right)}.$$

In 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

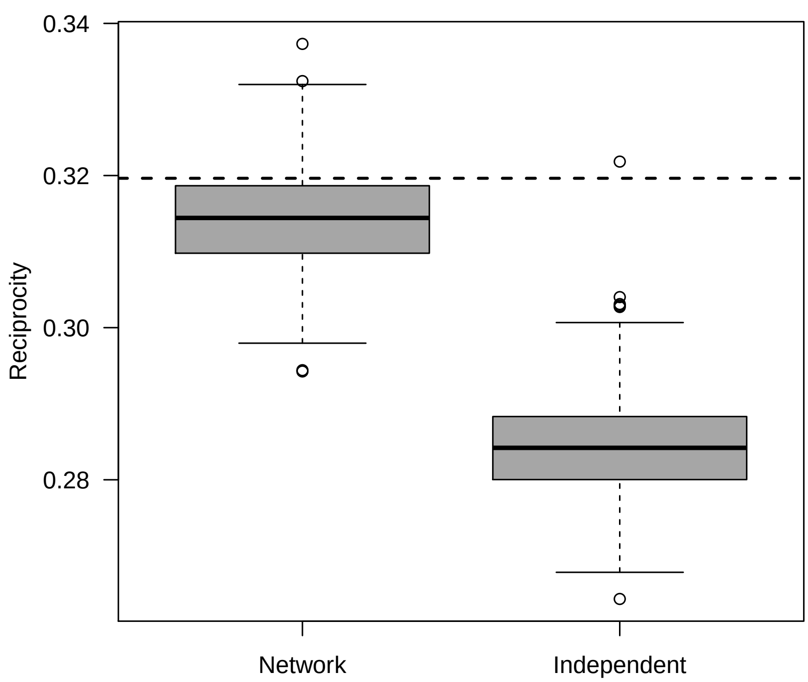


Figure 2: Reciprocity values of 1,000 networks simulated from the Network and Independent models. Observed value given by the dashed horizontal line.

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 fit to 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 network structure. [17] The dependence effects, though formulated intuitively, do not permit a

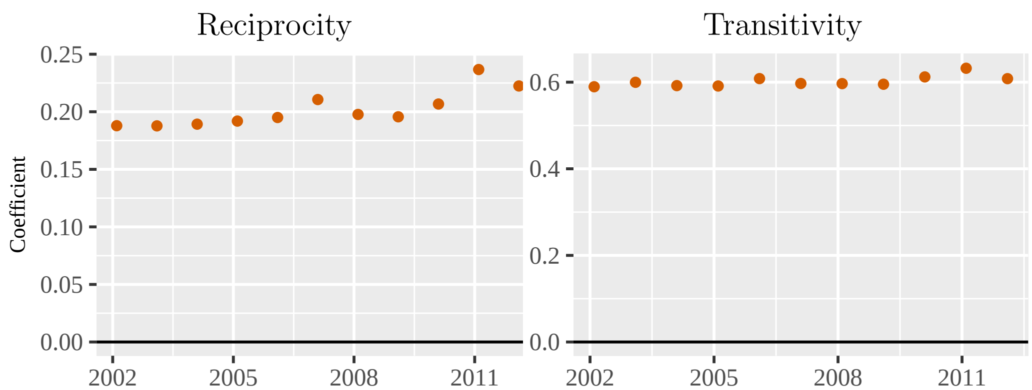


Figure 3: Estimates of Network terms in Poisson ERGMs. Bars span 95% confidence intervals.

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

[17] As noted in the Section 4.1, 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 mutuality 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 the level of development between dyads.

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.

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.

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 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 the network model, we find the following effects to be lower in magnitude, statistically significant in fewer years, or both: Gravity model mass,

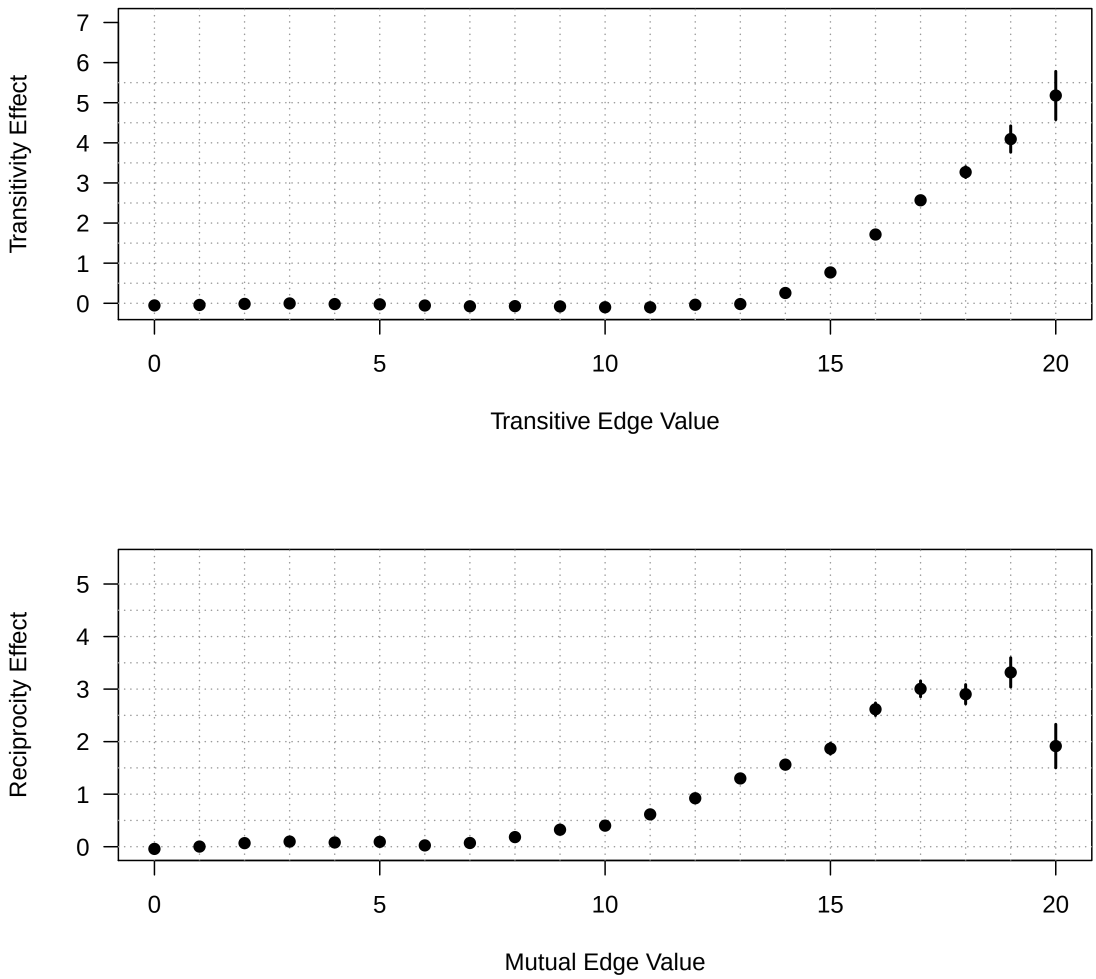
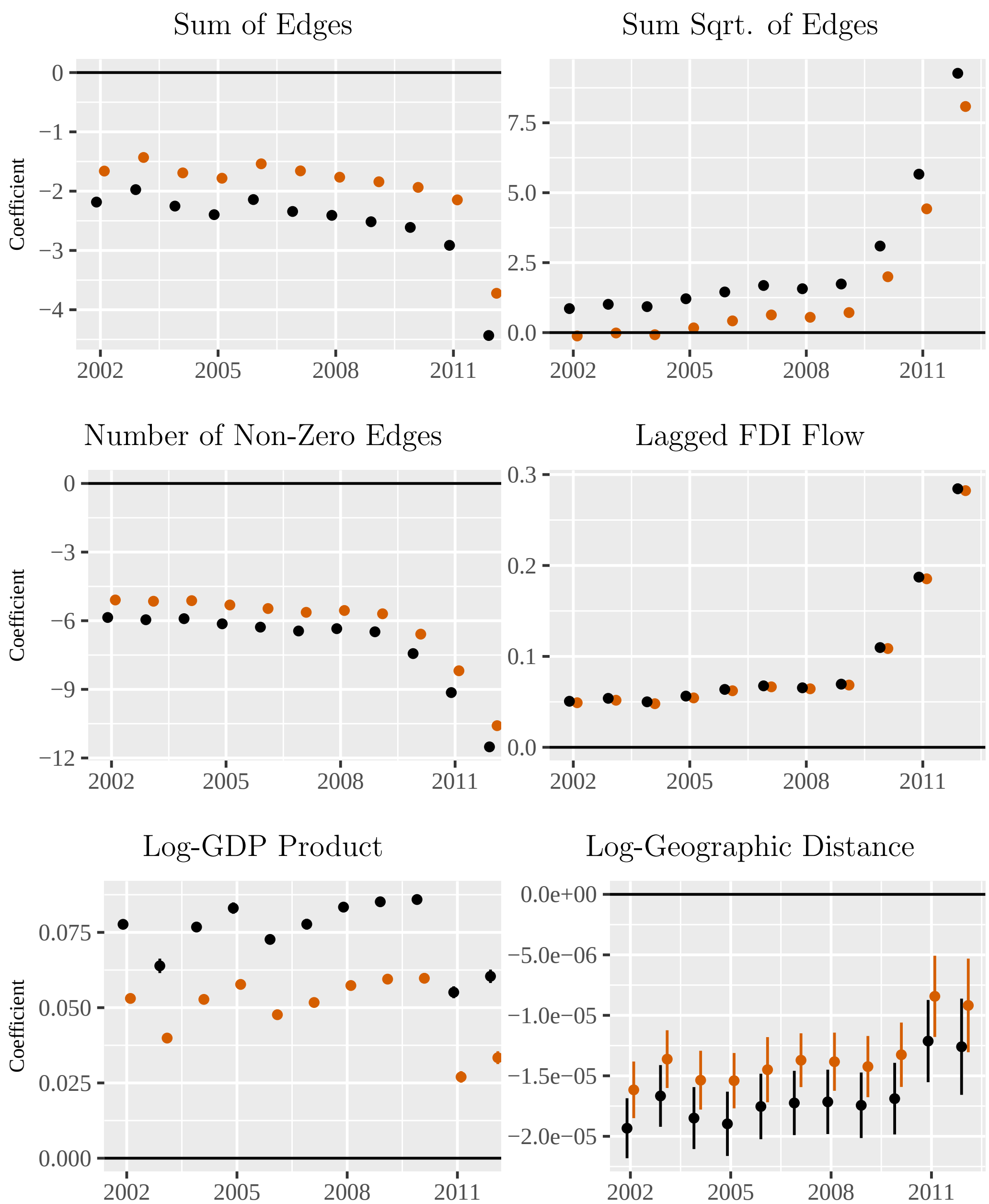
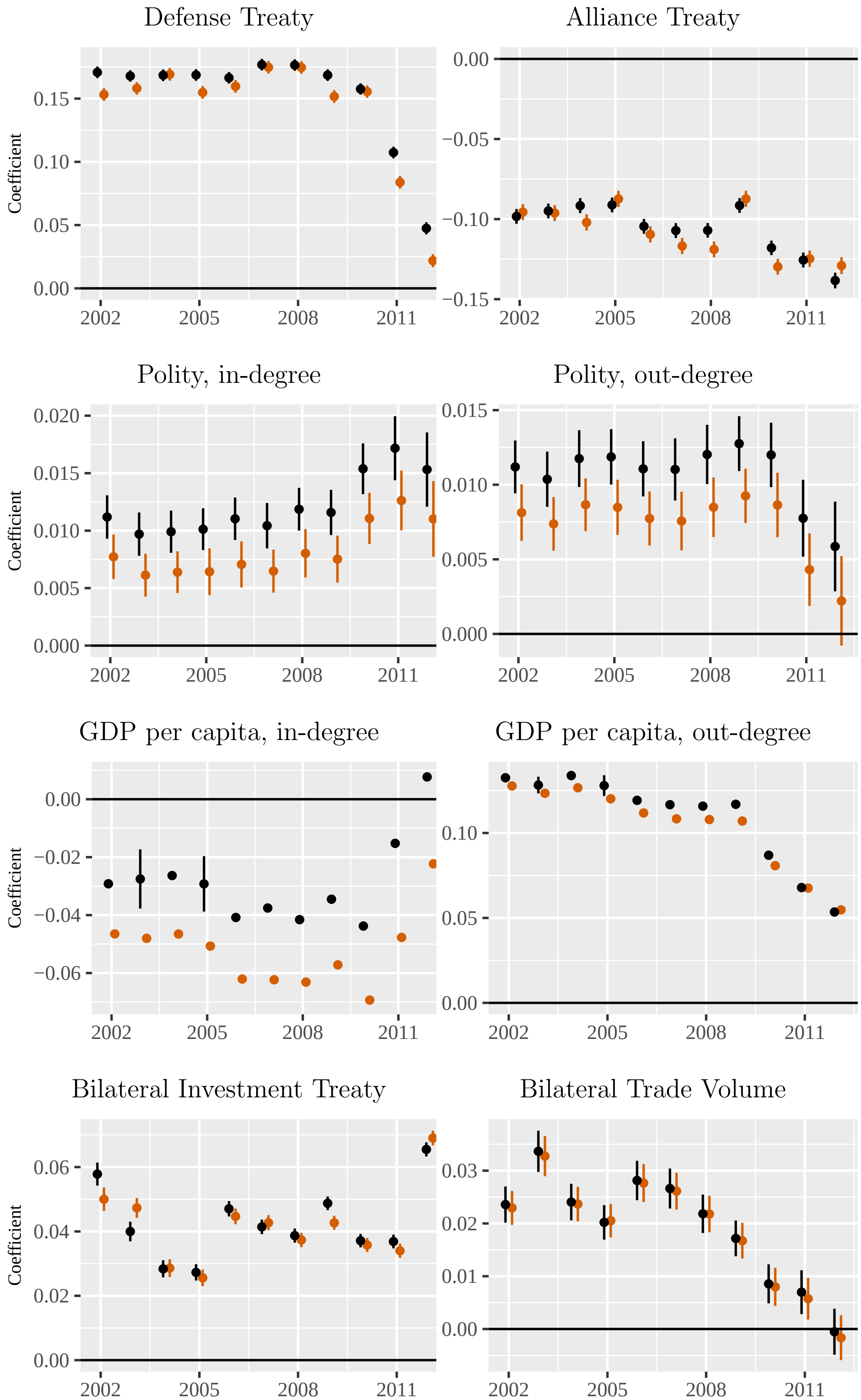


Figure 4: Plots depict the difference in predicted value (y-axis) that is attributable to the respective dependence effect, averaged over all dyads in the network. Interpretation plots are based on 1,000 FDI stock networks simulated from the 2012 model. Tie weights are measured on the natural logarithm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

distance, contiguity, PTA depth, 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.


Sum of Edges
Sum Sqrt. of Edges
Number of Non-Zero Edges
Lagged FDI Flow
Log-GDP Product
Log-Geographic Distance
Coefficient
0
−1
−2
−3
−4
7.5
5.0
2.5
0.0
−6
−9
−12
0.3
0.2
0.1
0.075
0.050
0.025
0.000
0.0e+00
−5.0e−06
−1.0e−05
−1.5e−05
−2.0e−05
2002
2005
2008
2011


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
Coefficient
2002
2005
2008
2011

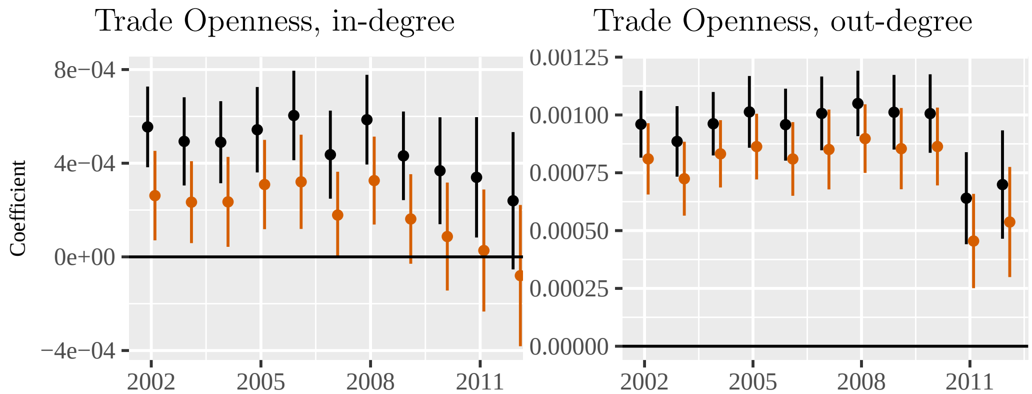


Table 1: Estimates of exogenous terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).

4.1 Ripple effects of FDI shocks

When it comes to the analysis of the international political economy, one of the central advantages of the network scientific 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 $i \rightarrow j$ 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. These edges are "close" to edge $i \rightarrow j$ 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 $i \rightarrow j$. 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.

The results from our simulation exercise are presented in Figure 5. 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

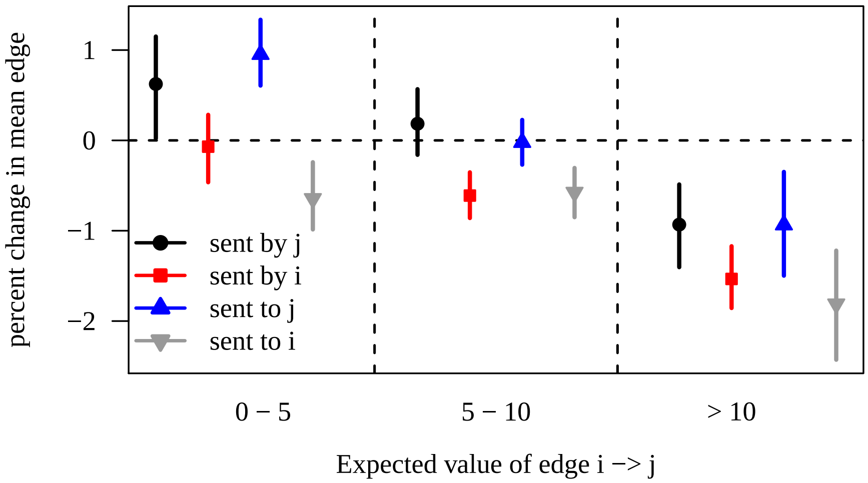


Figure 5: Results from simulation exercise investigating the effects of eliminating edge $i \to j$ on the expected values of other edges incident to both i and j. Points are drawn at the average values over all edges in the 2012 network. The bars span 95% nonparametric bootstrap confidence intervals, which are constructed by resampling edges. Expected values of edges are expressed on the natural logarithm scale.

($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 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 $i \to j$ 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

Over recent decades, 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.[18] It is important to

[18]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 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.

References

Abrahamowicz, M and A Ciampi. 1990. Optimal Fit in Non-Parametric Modelling Via Computationally Intensive Inference. In *Compstat*. Springer pp. 309–314.

Aizenman, Joshua and Ilan Noy. 2006. "FDI and trade: Two-way linkages?" *The Quarterly Review of Economics and Finance* 46(3):317–337.

Allee, Todd and Clint Peinhardt. 2011. "Contingent Credibility: The Impact of Investment Treaty Violations on Foreign Direct Investment." *International Organization* 65(3):401–432.

Axelrod, Robert M. 1984. *The Evolution of Cooperation*. New York: Basic Books.

Bagwell, Kyle and Robert W. Staiger. 1999. "An Economic Theory of GATT." *The American Economic Review* 89(1):215–248.

Baldwin, Richard. 2011. "Trade And Industrialisation After Globalisation's 2^{nd} Unbundling: How Building And Joining A Supply Chain Are Different And Why It Matters." *National Bureau of Economic Research Working Paper Series* No. 17716.

Beazer, Quintin H. and Daniel J. Blake. 2018. "The Conditional Nature of Political Risk: How Home Institutions Influence the Location of Foreign Direct Investment." *American Journal of Political Science* (Online Early View).

Boehmke, Frederick J, Olga Chyzh and Cameron G Thies. 2016. "Addressing endogeneity in actor-specific network measures." *Political Science Research and Methods* 4(01):123–149.

Brida, Juan Gabriel, David Matesanz Gómez and Wiston Adrián Risso. 2009. "Symbolic hierarchical analysis in currency markets: An application to contagion in currency crises." *Expert Systems with applications* 36(4):7721–7728.

Büthe, Tim and Helen V. Milner. 2008. "The Politics of Foreign Direct Investment into Developing Countries: Increasing FDI through International Trade Agreements?" *American Journal of Political Science* 52(4):741–762.

Büthe, Tim and Helen V Milner. 2014. "Foreign direct investment and institutional diversity in trade agreements: Credibility, commitment, and economic flows in the developing world, 1971–2007." *World Politics* 66(01):88–122.

Cao, Xun and Michael D Ward. 2014. "Do democracies attract portfolio investment? Transnational portfolio investments modeled as dynamic network." *International Interactions* 40(2):216–245.

Carr, David L., James R. Markusen and Keith E. Maskus. 2001. "Estimating the Knowledge-Capital Model of the Multinational Enterprise." *The American Economic Review* 91(3):693–708.

Caves, Richard E. 1996. *Multinational Enterprise and Economic Analysis*. New York: Cambridge University Press.

Chilton, Adam S., Helen V. Milner and Dustin Tingley. Forthcoming. "Reciprocity and Public Opposition to Foreign Direct Investment." *British Journal of Political Science* .

Chuluun, Tuugi. 2017. "Global portfolio investment network and stock market comovement." *Global Finance Journal* 33:51–68.

Cranmer, Skyler J and Bruce A Desmarais. 2011. "Inferential network analysis with exponential random graph models." *Political Analysis* pp. 66–86.

Cranmer, Skyler J and Bruce A Desmarais. 2016. "A critique of dyadic design." *International Studies Quarterly* 60(2):355–362.

Cranmer, Skyler J, Bruce A Desmarais and Justin H Kirkland. 2012. "Toward a network theory of alliance formation." *International Interactions* 38(3):295–324.

Cranmer, Skyler J, Philip Leifeld, Scott D McClurg and Meredith Rolfe. 2016. "Navigating the range of statistical tools for inferential network analysis." *American Journal of Political Science* .

Cranmer, Skyler J, Tobias Heinrich and Bruce A Desmarais. 2014. "Reciprocity and the structural determinants of the international sanctions network." *Social Networks* 36:5–22.

Crystal, Jonathan. 2003. *Unwanted Company: Foreign Investment in American Industries*. Ithaca, NY: Cornell University Press.

Desmarais, Bruce A and Skyler J Cranmer. 2012. "Statistical inference for valued-edge networks: the generalized exponential random graph model." *PloS one* 7(1):e30136.

Desmarais, Bruce A. and Skyler J. Cranmer. 2017. Statistical Inference in Political Networks Research. In *The Oxford Handbook of Political Networks*, ed. Jennifer Nicoll Victor, Alexander H. Montgomery and Mark Lubell. Oxford University Press.

DiMascio, Nicholas and Joost Pauwelyn. 2008. "Nondiscrimination in Trade and Investment Treaties: Worlds Apart or Two Sides of the Same Coin?" *The American Journal of International Law* 102(1):48–89.

Dorussen, Han and Hugh Ward. 2008. "Intergovernmental Organizations and the Kantian Peace." *Journal of Conflict Resolution* 52(2):189–212.

Dorussen, Han and Hugh Ward. 2010. "Trade networks and the Kantian peace." *Journal of Peace Research* 47(1):29–42.

Dunning, John H. 1988. "The Eclectic Paradigm of International Production: A Restatement and Some Possible Extensions." *Journal of International Business Studies* 19(1):1–31.

Dunning, John H. 1992. *Multinational Enterprises and the Global Economy*. Reading, MA: Addison-Wesley.

Eden, Lorraine and Stewart R Miller. 2004. "Distance Matters: Liability of Foreignness, Institutional Distance and Ownership Strategy." *Advances in International Management* 16:187–221.

Feenstra, Robert C, Robert Inklaar and Marcel P Timmer. 2015. "The next generation of the Penn World Table." *The American Economic Review* 105(10):3150–3182.

Frenkel, Michael, Katja Funke and Georg Stadtmann. 2004. "A Panel Analysis of Bilateral FDI Flows to Emerging Economies." *Economic Systems* 28(3):281–300.

Gai, Prasanna and Sujit Kapadia. 2010. Contagion in financial networks. In *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*. Vol. 466 The Royal Society pp. 2401–2423.

Garlaschelli, Diego and Maria I Loffredo. 2004. "Patterns of link reciprocity in directed networks." *Physical Review Letters* 93(26):268701.

Gibler, Douglas M. 2009. "International military alliances, 1648-2008.". CQ Press.

Graham, Edward M. 1978. "Transatlantic Investment by Multinational Firms: A Rivalistic Phenomenon?" *Journal of Post Keynesian Economics* 1(1):82–99.

Handcock, Mark S., David R. Hunter, Carter T. Butts, Steven M. Goodreau, Pavel N. Krivitsky and Martina Morris. 2017. *ergm: Fit, Simulate and Diagnose Exponential-Family Models for Networks*. The Statnet Project (`http://www.statnet.org`). R package version 3.6.1.
URL: *https://CRAN.R-project.org/package=ergm*

Helpman, Elhanan. 1984. "A Simple Theory of International Trade with Multinational Corporations." *The Journal of Political Economy* 92(3):451–471.

Helpman, Elhanan, Marc J. Melitz and Stephen R. Yeaple. 2004. "Export versus FDI with Heterogeneous Firms." *The American Economic Review* 94(1):300–316.

Henisz, Witold J. 2000. "The Institutional Environment for Multinational Investment." *The Journal of Law, Economics, & Organization* 16(2):334–364.

Holland, Paul W and Samuel Leinhardt. 1971. "Transitivity in Structural Models of Small Groups." *Small Group Research* 2(2):107–124.

Honaker, James, Gary King, Matthew Blackwell et al. 2011. "Amelia II: A program for missing data." *Journal of statistical software* 45(7):1–47.

Hymer, Stephen H. 1976. *The International Operations of National Firms: A Study of Direct Foreign Investment*. Cambridge, MA: MIT Press.

Jakobsen, Jo and Indra De Soysa. 2006. "Do Foreign Investors Punish Democracy? Theory and Empirics, 1984?C2001." *Kyklos* 59(3):383–410.

Jensen, Nathan M. 2003. "Democratic Governance and Multinational Corporations: Political Regimes and Inflows of Foreign Direct Investment." *International Organization* 57(03):587–616.

Jensen, Nathan M. 2006. *Nation-States and the Multinational Corporation: A Political Economy of Foreign Direct Investment*. Princeton, N.J.: Princeton University Press.

Johns, Leslie and Rachel L Wellhausen. 2016. "Under one roof: Supply chains and the protection of foreign investment." *American Political Science Review* 110(01):31–51.

Julius, DeAnne S. 1990. *Global Companies & Public Policy: The Growing Challenge of Foreign Direct Investment*. New York: The Council on Foreign Relations for the Royal Institute of International Affairs.

Kali, Raja and Javier Reyes. 2010. "Financial contagion on the international trade network." *Economic Inquiry* 48(4):1072–1101.

Kaminski, Bart and Beata Javorcik. 2005. Linkages between Foreign Direct Investment and Trade Flows. In *From Disintegration to Reintegration: Eastern Europe and the Former Soviet Union in International Trade*, ed. Harry G. Broadman. Washington, DC: World Bank pp. 337–374.

Keohane, Robert O. 1984. *After Hegemony: Cooperation and Discord in the World Political Economy*. Princeton, N.J.: Princeton University Press.

Kerner, Andrew. 2009. "Why Should I Believe You? The Costs and Consequences of Bilateral Investment Treaties." *International Studies Quarterly* 53(1):73–102.

Kim, Soo Yeon and Etel Solingen. 2017. "Production Networks and Conflict in East Asia.". Paper Presented at the Annual Meeting of International Political Economy Society. Available at `https://www.internationalpoliticaleconomysociety.org/sites/default/files/paper-uploads/2017-11-15-17_30_32-sooyeon.kim@nus.edu.sg.pdf`.

Kindleberger, Charles P. 1969. *American Business Abroad: Six Lectures on Direct Investment*. New Haven, CT: Yale University Press.

Kirkland, Justin H. 2013. "Hypothesis testing for group structure in legislative networks." *State Politics & Policy Quarterly* 13(2):225–243.

Kostova, Tatiana and Srilata Zaheer. 1999. "Organizational Legitimacy under Conditions of Complexity: The Case of the Multinational Enterprise." *Academy of Management review* 24(1):64–81.

Krivitsky, Pavel N. 2012. "Exponential-family random graph models for valued networks." *Electronic Journal of Statistics* 6:1100.

Krivitsky, Pavel N. 2016. *ergm.count: Fit, Simulate and Diagnose Exponential-Family Models for Networks with Count Edges*. The Statnet Project (`http://www.statnet.org`). R package version 3.2.2.
URL: *http://CRAN.R-project.org/package=ergm.count*

Kwok, Chuck C. Y. and Solomon Tadesse. 2006. "The MNC as an Agent of Change for Host-Country Institutions: FDI and Corruption." *Journal of International Business Studies* 37(6):767–785.

Lagunoff, Roger and Stacey L Schreft. 2001. "A model of financial fragility." *Journal of Economic Theory* 99(1-2):220–264.

Leblang, David. 2010. "Familiarity Breeds Investment: Diaspora Networks and International Investment." *American Political Science Review* 104(03):584–600.

Leifeld, Philip. 2013. "Reconceptualizing major policy change in the advocacy coalition framework: a discourse network analysis of German pension politics." *Policy Studies Journal* 41(1):169–198.

Leitner, Yaron. 2005. "Financial networks: Contagion, commitment, and private sector bailouts." *The Journal of Finance* 60(6):2925–2953.

Li, Quan and Adam Resnick. 2003. "Reversal of Fortunes: Democratic Institutions and Foreign Direct Investment Inflows to Developing Countries." *International Organization* 57(01):175–211.

Li, Quan, Erica Owen and Austin Mitchell. 2016. "Do Democracies Attract More Foreign Direct Investment? A Meta Regression Analysis.". Paper Presented at the Annual Meeting of American Political Science Association.

Li, Quan and Tatiana Vashchilko. 2010. "Dyadic Military Conflict, Security Alliances, and Bilateral FDI Flows." *Journal of International Business Studies* 41(5):765–782.

Markusen, James R. 1995. "The Boundaries of Multinational Enterprises and the Theory of International Trade." *The Journal of Economic Perspectives* 9(2):169–189.

Marshall, Monty G. and Keith Jaggers. 2010. "Polity IV Project: Political Regime Characteristics and Transitions, 1800-2008.".

Matesanz, David and Guillermo J Ortega. 2014. "Network analysis of exchange data: interdependence drives crisis contagion." *Quality & Quantity* 48(4):1835–1851.

Mayer, Thierry and Soledad Zignago. 2011. "Notes on CEPII's distances measures: The GeoDist database.".

Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71(6):1695–1725.

Moran, Theodore. 2014. "Foreign Investment and Supply Chains in Emerging Markets: Recurring Problems and Demonstrated Solutions." *Peterson Institute for International Economics Working Paper* No. 2014-12.

OECD. 2016. "Bilateral Trade in Goods by Industry and End-use (BTDIxE), ISIC Rev.4.".

Pandya, Sonal S. 2016. "Political Economy of Foreign Direct Investment: Globalized Production in the Twenty-First Century." *Annual Review of Political Science* 19:455–475.

R Core Team. 2015. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.
URL: *https://www.R-project.org/*

Raftery, Adrian E. 1999. "Bayes factors and BIC: Comment on ?A critique of the Bayesian information criterion for model selection?" *Sociological Methods & Research* 27(3):411–427.

Razin, Assaf, Efraim Sadka and Hui Tong. 2005. Bilateral FDI Flows: Threshold Barriers and Productivity Shocks. Working Paper 11639 National Bureau of Economic Research.
URL: *http://www.nber.org/papers/w11639*

Resnick, Adam L. 2001. "Investors, Turbulence, and Transition: Democratic Transition and Foreign Direct Investment in Nineteen Developing Countries." *International Interactions* 27(4):381–398.

Sandholtz, Wayne and Mark M. Gray. 2003. "International Integration and National Corruption." *International Organization* 57(04):761–800.

Schiavo, Stefano, Javier Reyes and Giorgio Fagiolo. 2010. "International trade and financial integration: a weighted network analysis." *Quantitative Finance* 10(4):389–399.

Staats, Joseph L. and Glen Biglaiser. 2012. "Foreign Direct Investment in Latin America: The Importance of Judicial Strength and Rule of Law." *International Studies Quarterly* 56(1):193–202.

Tingley, Dustin, Christopher Xu, Adam Chilton and Helen V. Milner. 2015. "The Political Economy of Inward FDI: Opposition to Chinese Mergers and Acquisitions." *The Chinese Journal of International Politics* 8(1):27–57.

UNCTAD. 1991. *World Investment Report*. New York: United Nations.

UNCTAD. 2006. *FDI from Developing and Transition Economies: Implications for Development*. New York: United Nations.

UNCTAD. 2013. *Global Value Chains: Investment and Trade for Development*. New York: United Nations.

UNCTAD. 2014. *Bilateral FDI Statistics*. New York: United Nations.

Vernon, Raymond. 1971. *Sovereignty at Bay: The Multinational Spread of U.S. Enterprises.* New York: Basic Books.

Vernon, Raymond. 1980. The Obsolescing Bargain: A Key Factor in Political Risk. In *The International Essays for Business Decision Makers*, ed. Mark B. Winchester. Houston, T.X.: Center for International Business.

Waldorp, Lourens J, Hilde M Huizenga, Arye Nehorai, Raoul PPP Grasman and Peter CM Molenaar. 2005. "Model selection in spatio-temporal electromagnetic source analysis." *IEEE transactions on biomedical engineering* 52(3):414–420.

Ward, Michael D, John S Ahlquist and Arturas Rozenas. 2013. "Gravity's Rainbow: A dynamic latent space model for the world trade network." *Network Science* 1(1):95–118.

Ward, Michael D and Peter D Hoff. 2007. "Persistent patterns of international commerce." *Journal of Peace Research* 44(2):157–175.

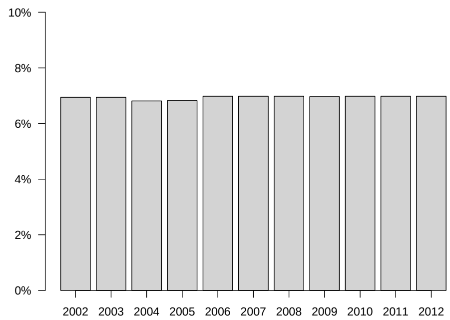
Wilson, James D, Matthew J Denny, Shankar Bhamidi, Skyler J Cranmer and Bruce A Desmarais. 2017. "Stochastic weighted graphs: Flexible model specification and simulation." *Social Networks* 49:37–47.

Zaheer, Srilata. 1995. "Overcoming the Liability of Foreignness." *Academy of Management Journal* 38(2):341–363.

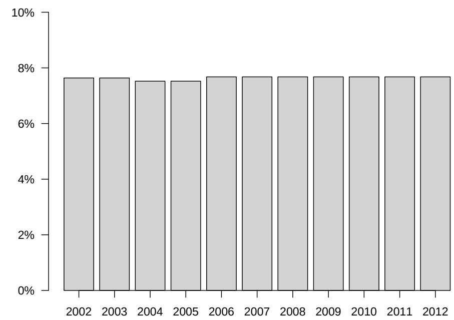
Zakaria, Firano and Filali Adib Fatine. 2017. "Evidence of the cross border contagion risk for Moroccan banking system." *Risk and Decision Analysis* 6(4):299–315.

A Summary Statistics

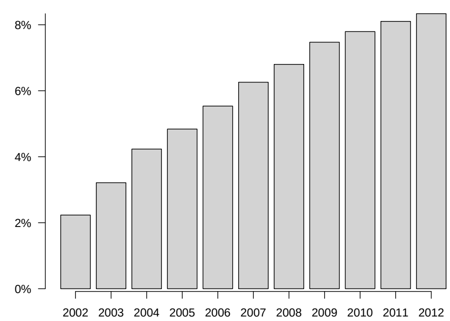
Alliance Treaty



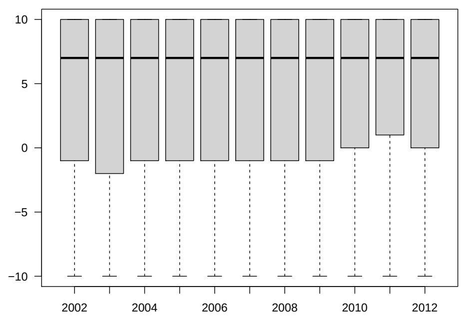
Defense Treaty



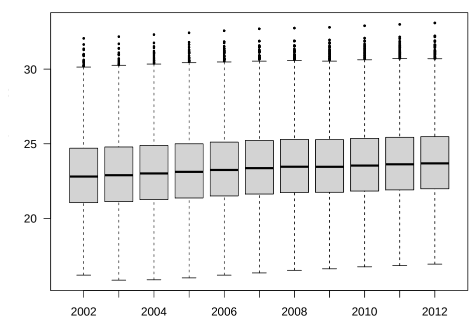
Bilateral Investment Treaty



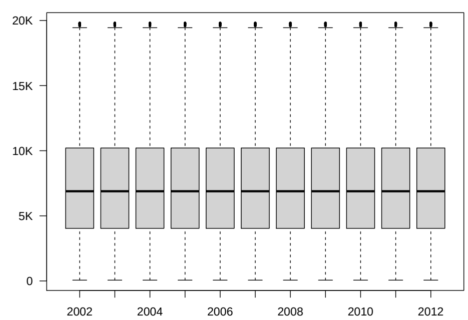
Polity



Dyad GDP Product



Distance



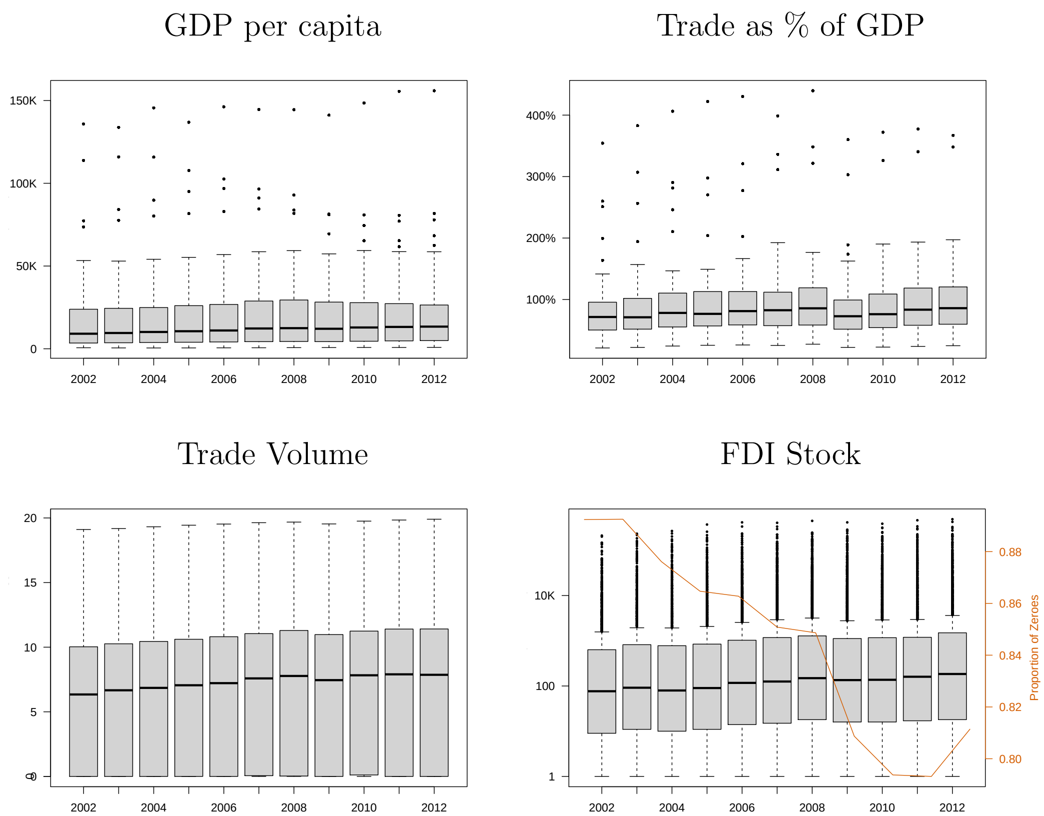


Table A: Summary Statistics.

Table B: Correlation Matrix

	Mass	Distance	Polity
Mass	1	-0.003	0.091
Distance (logged)	-0.003	1	0.008
Polity	0.091	0.008	1
Trade Openness	-0.166	-0.057	-0.078
BITs	0.141	-0.085	0.018
Trade Volume	0.714	-0.215	0.215
GDP per capita (logged)	0.392	-0.084	0.166
Alliance Treaty	0.133	-0.348	0.073
Defense Treaty	0.065	-0.391	0.065

	Trade Openness	BITs	Trade Volume
Mass	-0.166	0.141	0.714
Distance (logged)	-0.057	-0.085	-0.215
Polity	-0.078	0.018	0.215
Trade Openness	1	0.032	-0.055
BITs	0.032	1	0.143
Trade Volume	-0.055	0.143	1
GDP per capita (logged)	0.225	0.093	0.330
Alliance Treaty	-0.044	0.021	0.216
Defense Treaty	-0.046	0.010	0.177

	GDP per capita	Alliance Treaty	Defense Treaty
Mass	0.392	0.133	0.065
Distance	-0.084	-0.348	-0.391
Polity	0.166	0.073	0.065
Trade Openness	0.225	-0.044	-0.046
BITs	0.093	0.021	0.010
Trade Volume	0.330	0.216	0.177
GDP per capita (logged)	1	0.098	0.038
Alliance Treaty	0.098	1	0.850
Defense Treaty	0.038	0.850	1

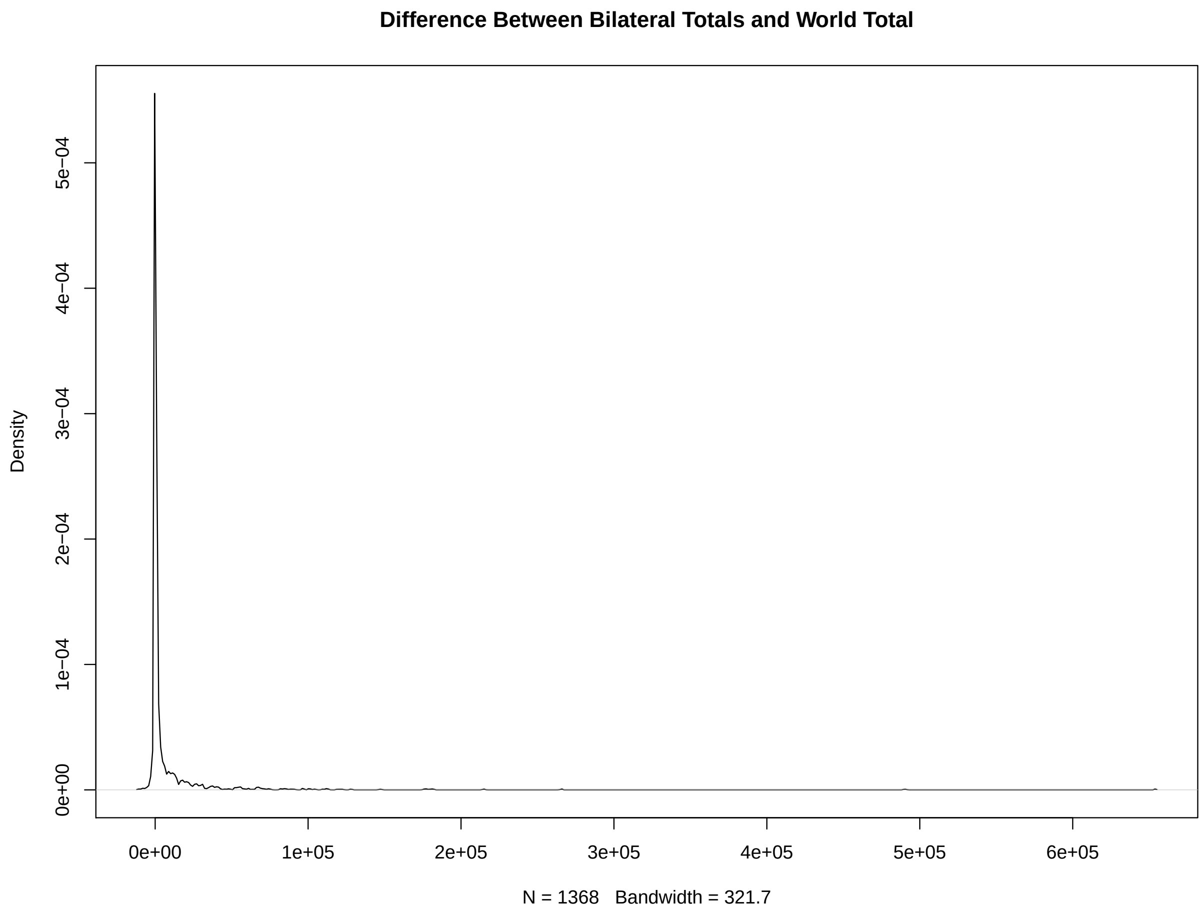


Figure A: Density Plot of the Difference between Total FDI stocks and Summing Bilateral FDI stocks.

B Time-Pooled Model Results

For robustness checks, we re-estimate the count ERGM by pooling the data, which is common in the literature for regression based models. Figure C shows that after pooling, network terms remain positive and statistically significant, supporting our hypothesis that reciprocity and transitivity characterize FDI flows. The exogenous covariates from the pooled model are presented in Table C. The estimates are similar to yearly results in terms of direction and statistical significance.

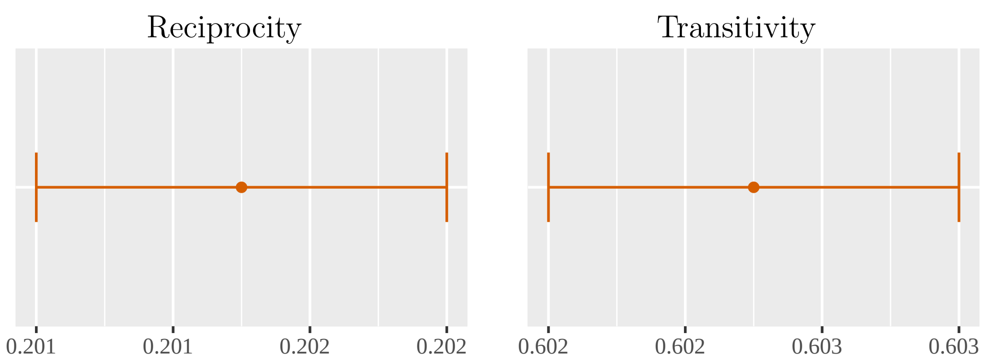
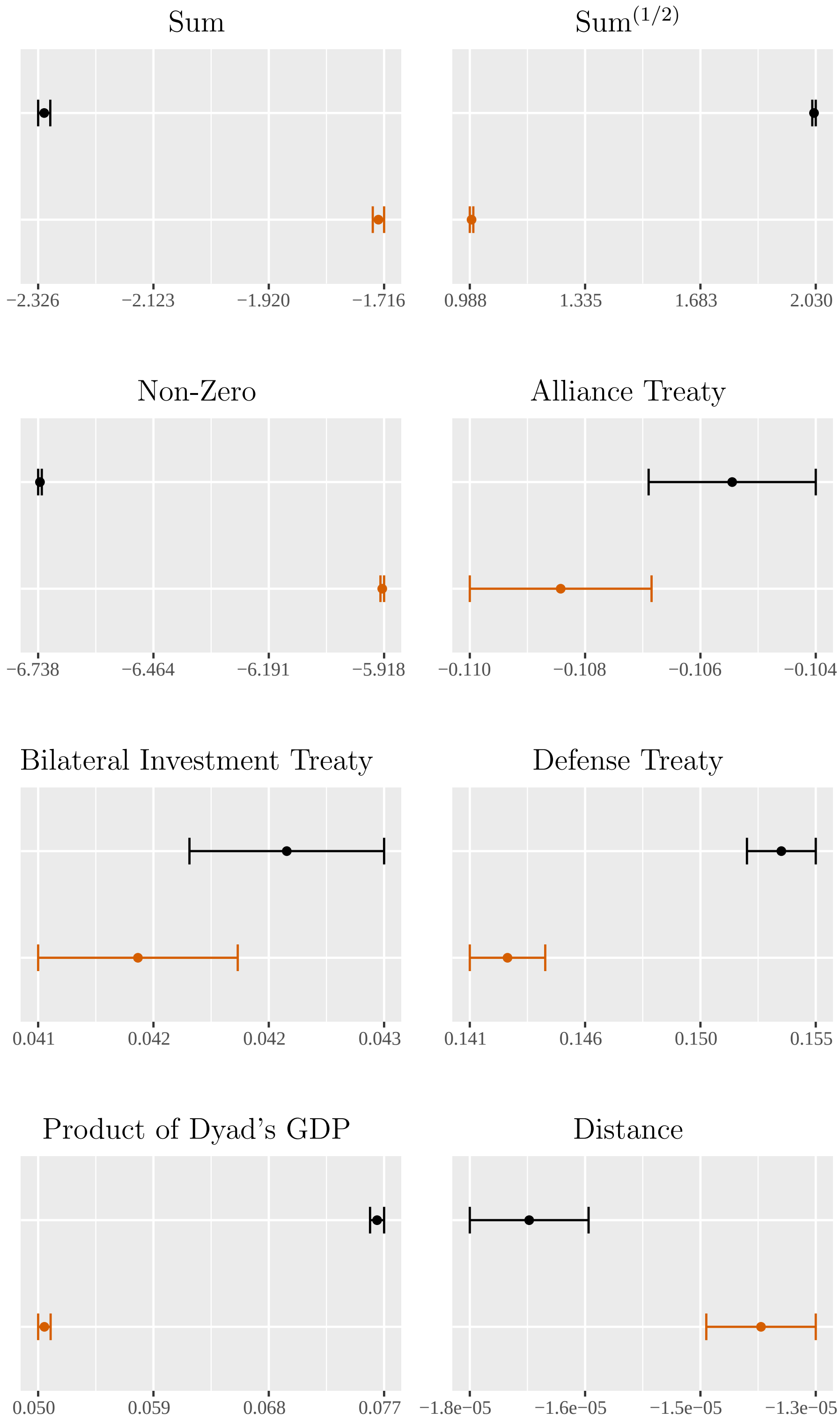


Figure B: Estimates of Dependence terms in time-pooled ERGMs. Bars span 95% confidence intervals.

The results also show that ignoring network structure lead to biased estimates in several covariates. We see significant differences in the coefficients for distance, the product of dyad's GDP, the three treaty variables, as well as origin and destination's GDP per capita, Polity, and trade openness. These findings are consistent with those from the yearly models. It illustrates that failure to include network structure results in biased estimates.


Sum
−2.326
−2.123
−1.920
−1.716
Sum$^{(1/2)}$
0.988
1.335
1.683
2.030
Non-Zero
−6.738
−6.464
−6.191
−5.918
Alliance Treaty
−0.110
−0.108
−0.106
−0.104
Bilateral Investment Treaty
0.041
0.042
0.042
0.043
Defense Treaty
0.141
0.146
0.150
0.155
Product of Dyad's GDP
0.050
0.059
0.068
0.077
Distance
−1.8e−05
−1.6e−05
−1.5e−05
−1.3e−05

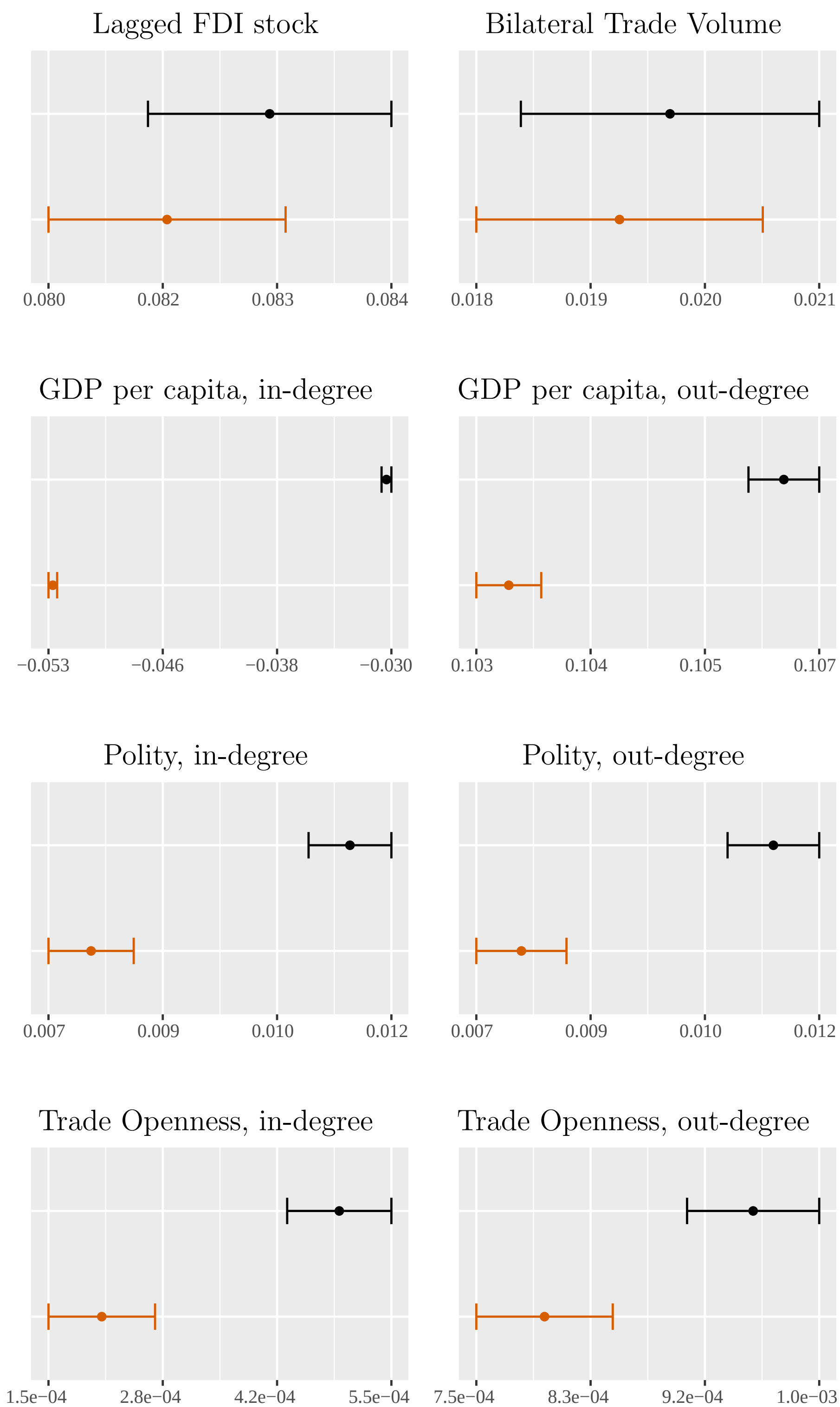


Table C: Estimates of terms in time-pooled ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).

C Subset by Missingness Results

To subset the data based on the level of missingness, we approximate total level of missingness (q) in the adjacency matrices by using the proportion of missing values for each node (p). When $p = 0.72$, $q \approx 0.25$ and $n = 28$. When $p = 0.86$, $q \approx 0.50$ and $n = 70$.

C.1 q ≈ 0.50

Figure C: Estimates of Dependence terms. Bars span 95% confidence intervals.

C.2 q ≈ 0.25

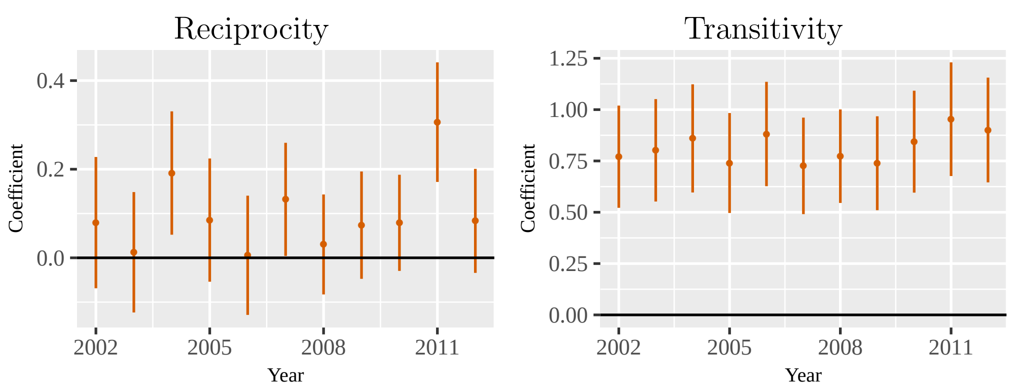


Figure D: Estimates of Dependence terms. Bars span 95% confidence intervals.

D Multiple Imputations with Amelia Results

We use the R Amelia package to create 10 datasets of imputed FDI stock values for the full dataset and when $q \approx 0.05$ (Honaker, King, Blackwell et al., 2011).

D.1 Full

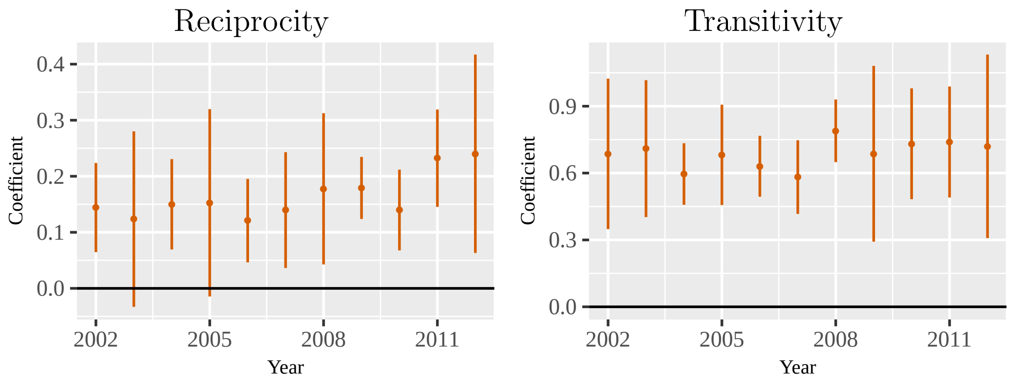


Figure E: Estimates of Dependence terms Bars span 95% confidence intervals.

D.2 q $\approx$ 0.50

Figure F: Estimates of Dependence terms in time-pooled ERGMs. Bars span 95% confidence intervals.