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

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Abstract

We study the structure of the international network of foreign direct investment (FDI). Existing studies of FDI?based on regression models?overlook the complex dependencies that are likely to characterize the FDI network. Recent developments in methodology for studying international relations show that regression is inadequate for quantitatively modeling dyadic data. We integrate hypotheses regarding exogenous covariate determinants and structural network dependencies into an exponential random graph model (ERGM) for weighted networks. We find that the FDI network exhibits both reciprocity and transitivity. These dependencies have been omitted from previous empirical models of FDI, which has consequences for inferences regarding covariate effects. In addition to our substantive findings, we offer a broad methodological contribution by introducing the ERGM for count-weighted networks in political science.

Pre-submission to-do

- ~~reduce abstract to 125 words~~
- ~~Do a general read through for grammar~~
- ~~Why don't we pool? With dyadic data we can identify effects. See significant heterogeneity. Beginning in 2008 we see a shift. This may be attributable to the great recession.~~
- Figures re-ordered
- Correlation table in appendix.
- Total outward FDI

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1 Introduction

What accounts for the dyadic patterns of global foreign direct investment (FDI)? Standard economic models attribute cross-border capital movements primarily to relative factor endowments, market size, and transportation and trade cost (see, e.g., Helpman, 1984; Carr, Markusen and Maskus, 2001). Yet, footloose capital becomes immobile ex post and thus an "obsolescent bargain," which is vulnerable to host government's expropriation (Vernon, 1971, 1980). Building on this insight, the political economy of FDI literature emphasizes the importance of political institutions in constraining host government's opportunistic behavior. Scholars suggest that political constraints (Henisz, 2000), democratic governance (Jensen, 2003, 2006), rule of law (Li and Resnick, 2003; Staats and Biglaiser, 2012), and participation in international institutions (Büthe and Milner, 2008; Allee and Peinhardt, 2011) help to ensure policy credibility and provide investor protection, thereby luring in foreign investors.

To date, existing theories have focused exclusively on firm-level characteristics and home- and host-country economic and political parameters to explain cross-border FDI flows. One implicit assumption in these theories is that countries and dyads are independent of each other. This assumption, nonetheless, unlikely holds, given the intertwined links among multinational corporations (MNCs) and the expansion of global production networks (UNCTAD, 2013). If global FDI flows can arise endogenously from the network structure, existing political economy models of FDI remain incomplete by excluding high-order structural variables. Furthermore, neglecting network structure variables may lead to biased estimates or even invalid inferences (Cranmer and Desmarais, 2011*a*).

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 the fact that host governments tend to use a principle of reciprocity to regulate FDI inflows. Second, the expansion of global supply chains and the diffusion of preferential trade agreements (PTAs) drive the transitivity/clustering of investment activities. 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 inflows are reciprocal and transitive (i.e., strongly clustered), suggesting that cross-border FDI flows are *interdependent* and shaped by their network structure. We further show that ignoring high-order network structure variables can lead to biased estimates in standard panel regression models.

Our paper advances the literature in two important ways. First, this study is the first to examine FDI flows through a network approach. Our network theory suggests that FDI flows can be shaped by structures of interdependence—a class of generative processes that has been overlooked in the existing literature.[1] We show that adding network dependencies to the covariate-based model of FDI offers a robust improvement in model fit. We believe our network approach to the study of global investment flows has broad implications for other cross-border movements of aid, goods, services, people, etc., which are central themes in the IPE literature, and could be analyzed with the same approach that we adopt. 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, we use the count exponential random graph model (ERGM) (Krivitsky, 2012) to test our arguments. To our knowledge, this recent extension of ERGM has not yet been applied in political science research. As such, 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

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

with count-weighted ties (e.g., 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), 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 provide an overview of the assumption of independence in empirical research on FDI, and international relations in general. Following that, we present theoretical claims that 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 Independence Assumptions and the Study of FDI

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 this sense, direct investment or the establishment of a foreign affiliate is a decision made by a parent company. Yet, footloose capital becomes relatively immobile after investment takes place, and thus a hostage to the host government (Vernon, 1971, 1980). MNCs are thus ex post vulnerable to the host government's opportunistic behavior, such as asset expropriation or subtle policy changes that dampen firms' profitability. Adopting a neo-institutionalist approach, the political economy of FDI literature emphasizes the role of domestic and international institutions in preventing state's predatory behavior and ensuring credible commitment, thereby attracting FDI (e.g. Henisz, 2000; Jensen, 2003, 2006; Li and Resnick, 2003; Staats and Biglaiser, 2012; Büthe and Milner, 2008; Allee and Peinhardt, 2011; Kerner, 2009).

There is now an expansive empirical literature examining the determinants of FDI inflows (e.g., Noorbakhsh, Paloni and Youssef, 2001; Yeaple, 2003; Jensen, 2003; Li and Resnick, 2003; Büthe and Milner, 2008; Li and Vashchilko, 2010; Kerner, 2009; Wright and Zhu, 2017).[2] 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. As such, the political economy of FDI literature has focused on examining the impact of host countries' political and economic characteristics on FDI flows, while overlooking the structure parameters. 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.

The study of FDI is not unique in its reliance on the independence assumption. Historically, statistical models used in international relations have involved the implicit assumption that countries and dyads are independent of each other (Diehl and Wright, 2016; Ward and Hoff, 2007). In the conflict literature, hypotheses regarding the likelihood of interstate war are often tested using dyadic panel data without a close attention to high-order structural dependencies (e.g. Cranmer and Desmarais, 2011*b*).[3] Likewise, in the IPE literature a dyadic panel research design is a common practice in the studies of bilateral flows of trade (e.g. Mansfield, Milner and Rosendorff, 2000; Rose, 2004; Goldstein, Rivers and Tomz, 2007; Bliss and Russett, 1998; Gowa and Mansfield, 1993), capital (e.g. Li and Vashchilko, 2010; Leblang, 2010; Egger and Pfaffermayr, 2004), aid (e.g. Bueno de Mesquita and Smith, 2009), and migrants (e.g. Fitzgerald, Leblang and Teets, 2014). For instance, the well-known democratic trade hypothesis, i.e., whether democratic dyads trade more with each other than other types of dyads, is examined using dyadic panel data sets where pairs of nations are assumed to be independently distributed. [4]

This assumption is now widely viewed as dubious (see, e.g., Ward and Hoff, 2007; Chu-Shore, 2010; Cranmer and Desmarais, 2016; Dorff and Ward, 2013; Lee and Bai, 2013; Howell,

[2]See Pandya (2016) for a comprehensive review.

[3]Ward, Siverson and Cao (2007) and Ward and Hoff (2007) are notable exceptions.

[4]Erikson, Pinto and Rader (2014) point out that a dyadic panel research design results in overconfident significance tests in OLS regressions if observations are not independent. They propose randomization testing to adjust standard errors. In this paper, we directly model the structural characteristics of the examined dependent variable.

2013; Kinne, 2016). The negative consequences of erroneously assuming independence are two-fold. First, the model is misspecified, which leads to biased estimates and hypothesis tests for covariates included in the model. Second, researchers arrive at a limited theoretical scope in which they only consider the relationship between the dependent variable and covariates, and do not consider the influences that ties and countries have on each other. The methodological toolkit available to scholars of international relations has advanced well beyond conventional regression approaches, and now offers at least three prominent options for modeling interdependence in relational data—-stochastic actor oriented models (e.g., Camber Warren, 2010; Kinne, 2016, 2013, 2014; Warren, 2016), exponential random graph models (e.g., Cranmer, Desmarais and Menninga, 2012; Cranmer, Desmarais and Kirkland, 2012; Raeymaeckers and Kenis, 2016), and latent space models (e.g., Ward, Siverson and Cao, 2007; Ward, Ahlquist and Rozenas, 2013; Metternich et al., 2013). As such, it is quite methodologically feasible to move beyond questionable independence assumptions in the study of FDI, and global economic exchanges in general.

3 Dependence Hypotheses in FDI Flows

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, global production networks (GPNs), and preferential trade agreements (PTAs), which are central to the FDI process. Through consideration of the structure and function of MNCs, we derive a reciprocity (Garlaschelli 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 GPNs and PTAs, 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.

3.1 Reciprocity of FDI Flows

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). Yet, reciprocity embedded in traditional bilateral investment treaties (BITs) concerns more the equal treatment and protection of investors, not liberalization or exchanges of market opportunities (DiMascio and Pauwelyn, 2008, 56). The reciprocity of FDI, instead, stems from the fact that FDI represents an oligopolistic expansion strategy of MNCs (Hymer, 1976; Kindleberger, 1969). MNCs arise from exploiting their ownership-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 these 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, resulting in reciprocal flows of investment.[5]

Historically, global investment activities have been dominated by MNCs from developed countries and characterized by a pattern of two-way flows.[6] 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

[5]The reciprocal investment flows can also result from firms' rivalistic strategy in response to foreign entries. Foreign entry may generate disruptive effects in the market, which stimulates rivalrous expansion of local firms into the home market of the foreign firm 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).

[6]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).

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.[7]

MNCs' oligopolistic expansion often encounters opposition from both host governments and the public due to concerns about national security, market monopoly, and protection of indigenous firms. 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, thereby establishing or reinforcing reciprocity (Milner, 1988; Crystal, 2003). As Crystal (2003, 6) note, "they [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." Indeed, both governments and citizens' reactions to inward foreign investment follow a principle of reciprocity. Tingley et al. (2015) show that U.S. government officials are more likely to oppose Chinese firms' mergers and acquisitions when China has blocked U.S. investment. Recently, the India government is proposing 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."[8] Looking at mass support for FDI, recent experimental evidence shows that citizens are more likely to support foreign investment from countries that grant reciprocal market access (Chilton, Milner and Tingley, Forthcoming). Therefore, we hypothesize the following:

Hypothesis 1: FDI flows are reciprocal.

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

[8] 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.

3.2 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).Two factors are likely to drive the transitivity of investment activities—the expansion of global production networks and 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.[9] 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. 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

[9] 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).

Korea, France, and the United States.[10]

More importantly, global supply chains tie countries together and significantly increase the cost of governments' opportunistic behaviors—such as 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, 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. 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. 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.[11]

The diffusion of PTAs is likely to drive the clustering of direct investment activities as

[10] http://cepz.ningbo.gov.cn/cat/cat159/con_159_5310.html, Accessed June 7, 2017.

[11] 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.

well. The formation of a PTA eliminates trade barriers among member states. The removal of trade barriers allows MNCs to optimize their global supply chains and fragment its production stages within member states 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 of government interventions, discrimination, and expropriation (Büthe and Milner, 2008; Büthe and Milner, 2014), thereby making member states more attractive investment destinations to each other. PTAs therefore reinforce the transitive clustering of investment activities.

Hypothesis 2: FDI flows are likely to be transitive.

4 Data and Research Design

To test our hypotheses, we estimate a gravity model of FDI. The dependent variable is bilateral FDI stock. The data are from UNCTAD, covering the time-period of 2001 to 2012. 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. We take the natural log of the bilateral FDI stock variable to deal with the skewed distribution.

[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).

4.1 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. Henisz, 2000; Jensen, 2003; Li and Resnick, 2003; Jakobsen and De Soysa, 2006; Resnick, 2001). 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 (BIT). This binary variable is one if the pair have a stand alone bilateral investment treaty 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 (Büthe and Milner, 2008; Büthe and Milner, 2014).

In addition, we include two sets of international agreement variables. The first is a

[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*.

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]

4.2 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 and Hoff, 2007; Ward, Ahlquist and Rozenas, 2013); 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 et al., 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 et al., 2016; 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

[16]Summary statistics of the covariates is provided in Appendix A

to a dyadic regression model in which ties are assumed to be independent and identically distributed (Cranmer and Desmarais, 2011*a*). 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.

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

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

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,

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

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,

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

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.

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

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

The count ERGM estimates that we present below are estimated using the `ergm` (Handcock et al., 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., Cranmer, Heinrich and Desmarais (2014), Cranmer, Desmarais and Kirkland (2012), Cao and Ward (2014), and 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.

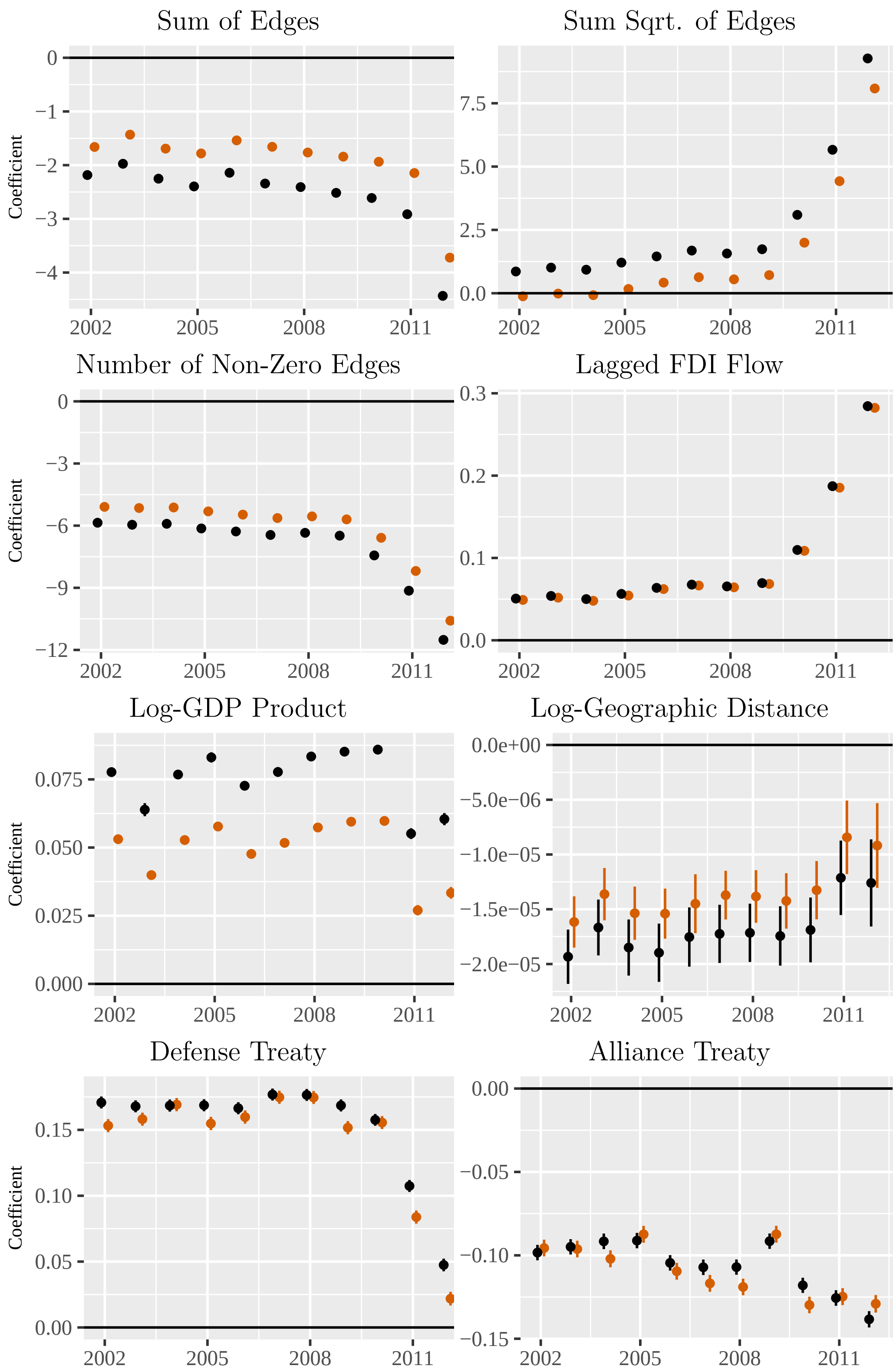

Figure 1: Estimates of exogenous terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).

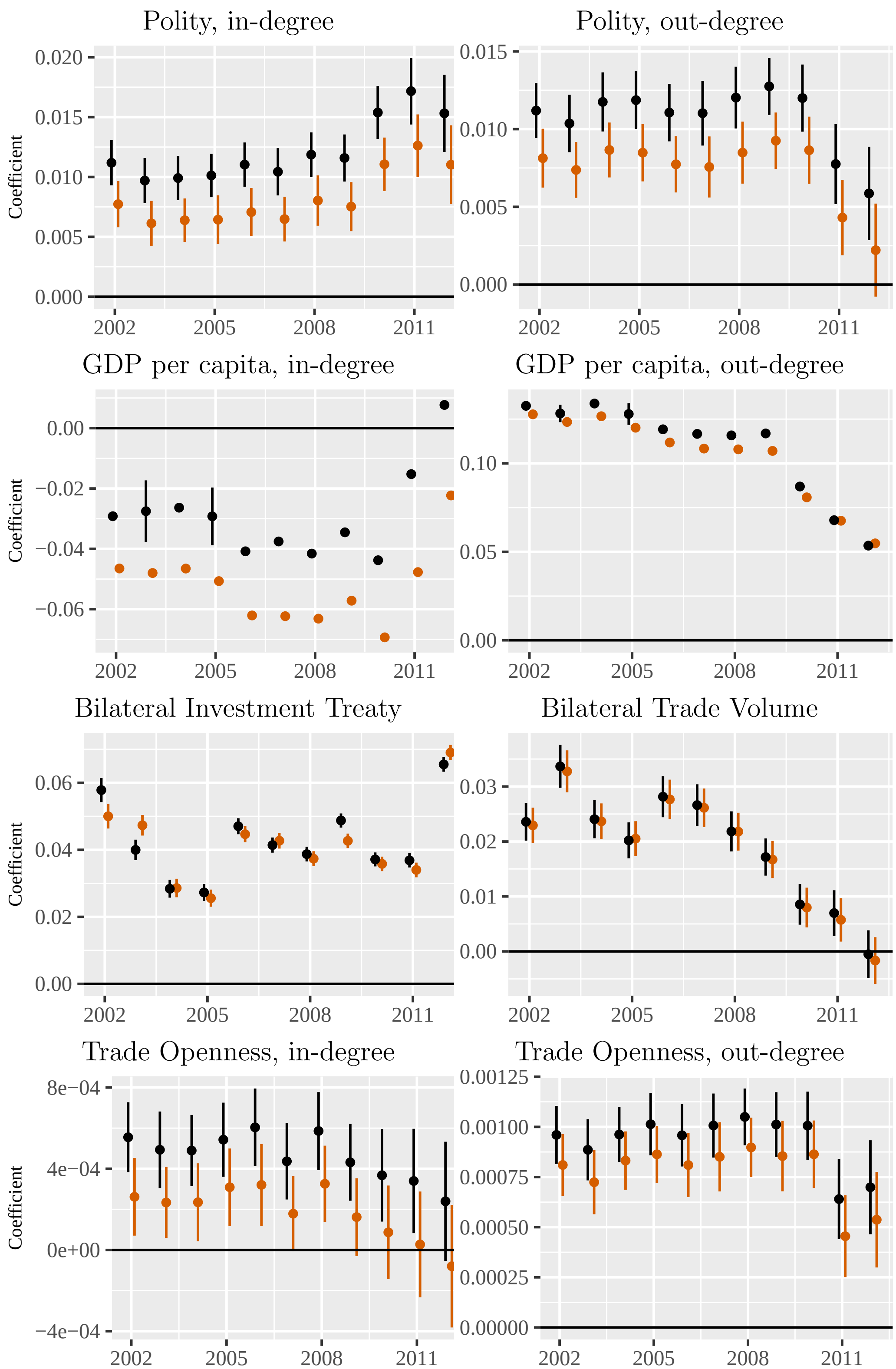

Figure 2: Estimates of exogenous terms in Poisson ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).

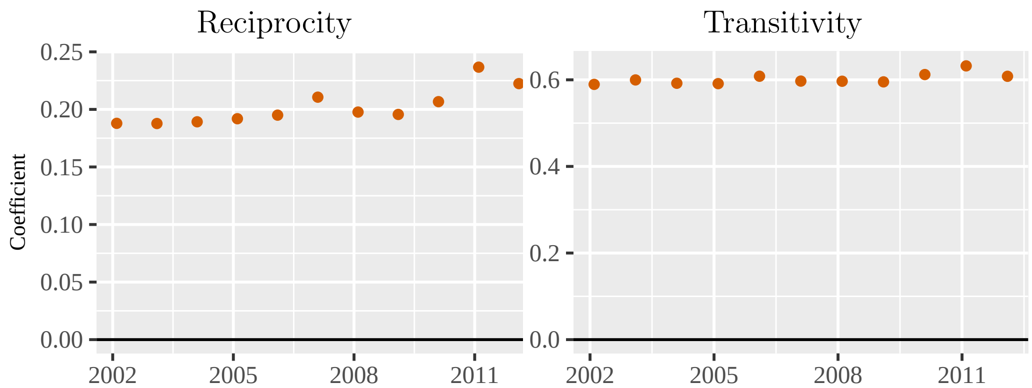

Figure 3: Estimates of Network terms in Poisson ERGMs. Bars span 95% confidence intervals.

5 Results

The coefficients estimated in the yearly count ERGMs are depicted in Figures 1–12. Before discussing individual effects, we first assess the relative fit of the independence and network models. Figure 7 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) (Waldorp et al., 2005; Abrahamowicz and Ciampi, 1990; Raftery, 1999). 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

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

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 5 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 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.

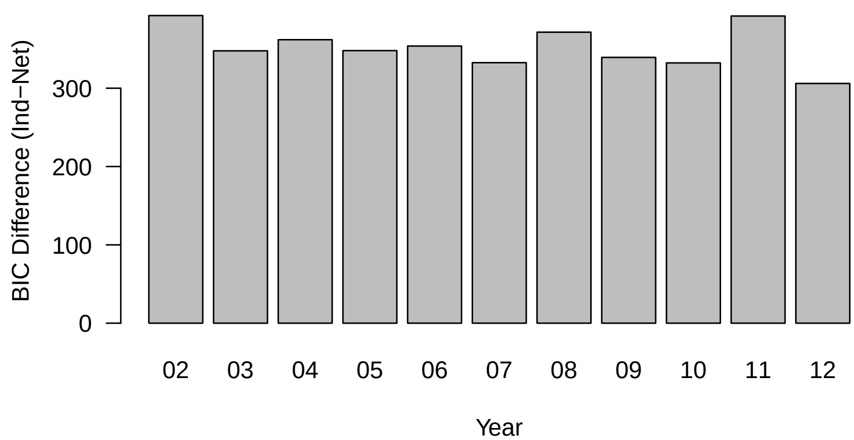

Figure 4: Difference in BIC between independent and network model.

Turning now to the network effects, which are presented in Figure 12, 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. 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 6 we present visualizations of the effects of the dependence terms. To measure these effects we begin with a simulation exercise in which we simulate networks using both the full model with dependence terms, and the null model based only on covariates. We then classify each simulated edge value in terms of the value of the local version of the dependence term operating on that edge. For example, when it comes to the reciprocity effect, we classify each simulated edge value ($y_{i,j}$) in terms of the value of the mutual edge, $y_{j,i}$. Finally, we estimate the difference in means between the edge values simulated from the full and null models at each dependence term value. This difference in means can be interpreted as the effect on predicted edge values of accounting for the respective dependence term in the model.

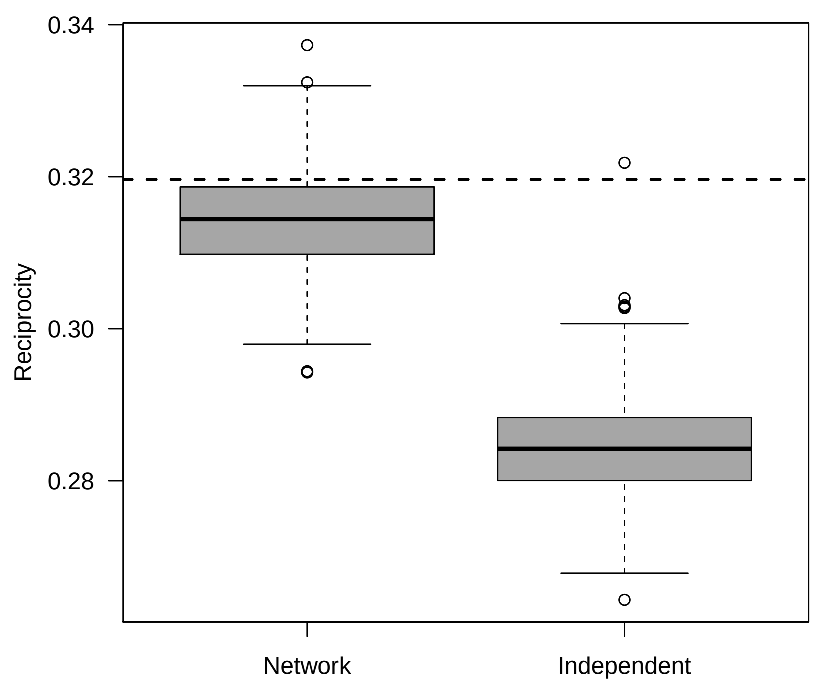

Figure 5: Reciprocity values of 1,000 networks simulated from the Network and Independent models. Observed value given by the dashed horizontal line.

We see in Figure 6, 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.

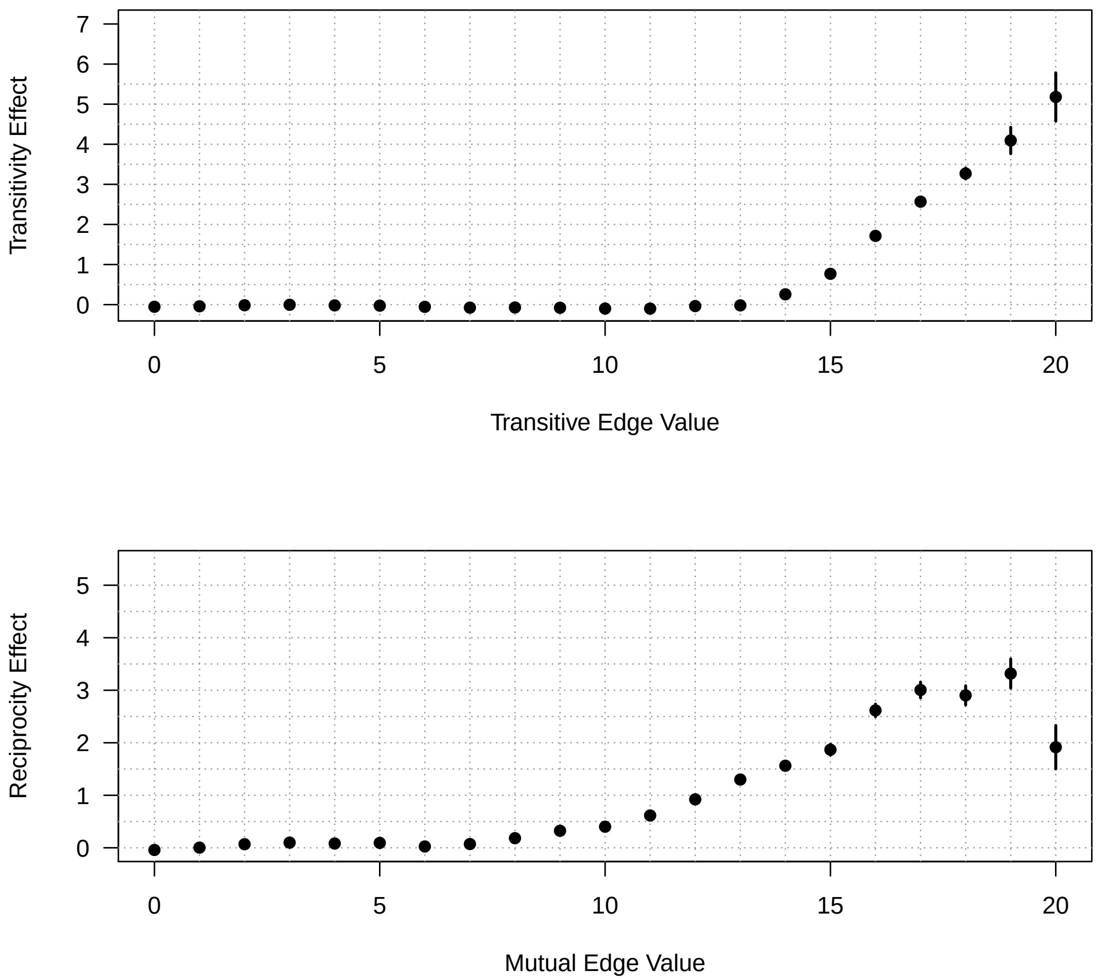

Figure 6: Plots depict the difference in predicted value (y-axis) that is attributable to the respective dependence effect, averaged over all dyads in the network. Interpretation plots are based on 1,000 FDI stock networks simulated from the 2012 model. Tie weights are measured on the natural logarithm 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.

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, 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 over-estimate 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 re-searcher is not theoretically interested in network dependencies, (s)he should still incorporate them into an empirical model in order to avoid misspecification bias.

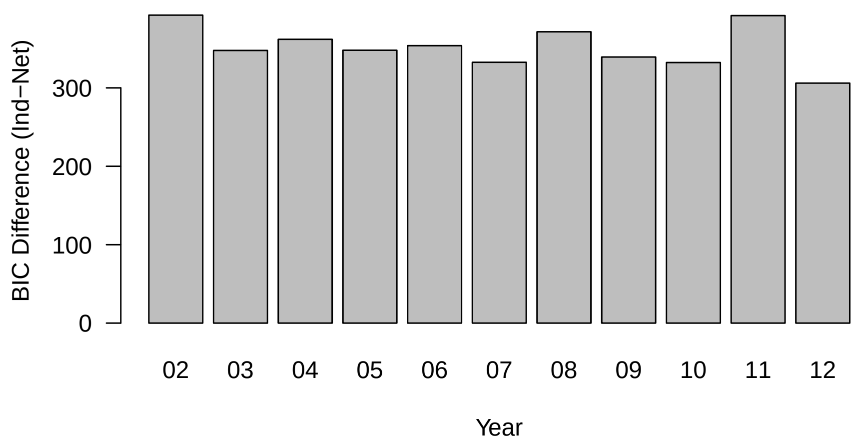

Figure 7: Difference in BIC between independent and network model.

6 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 drives 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.

Our result bears important real-world implications, as network dependencies will lead the effects of policies relevant to FDI to ripple through the network according to these dependencies. In FDI networks, a country's ability to attract foreign investment depends not only on its own locational advantages such as factor endowments, large consumer markets, or favorable government policies, but also on its connectivity to existing partner states in the network. As such, network dependencies will demand more policy coordination among nations, and thus, more likely to promote cooperation and peace by raising the opportunity cost of conflict.

Finally, 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 (Melitz, 2003; Helpman, Melitz and Yeaple, 2004). 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.[17] Future research can

[17]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

explore how network dependencies vary across different groups of countries.

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).

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A Summary Statistics

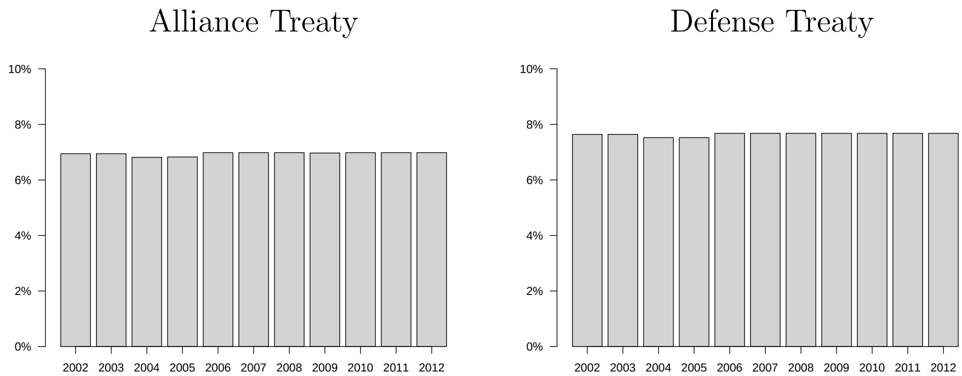

Figure 8: Summary Statistics.

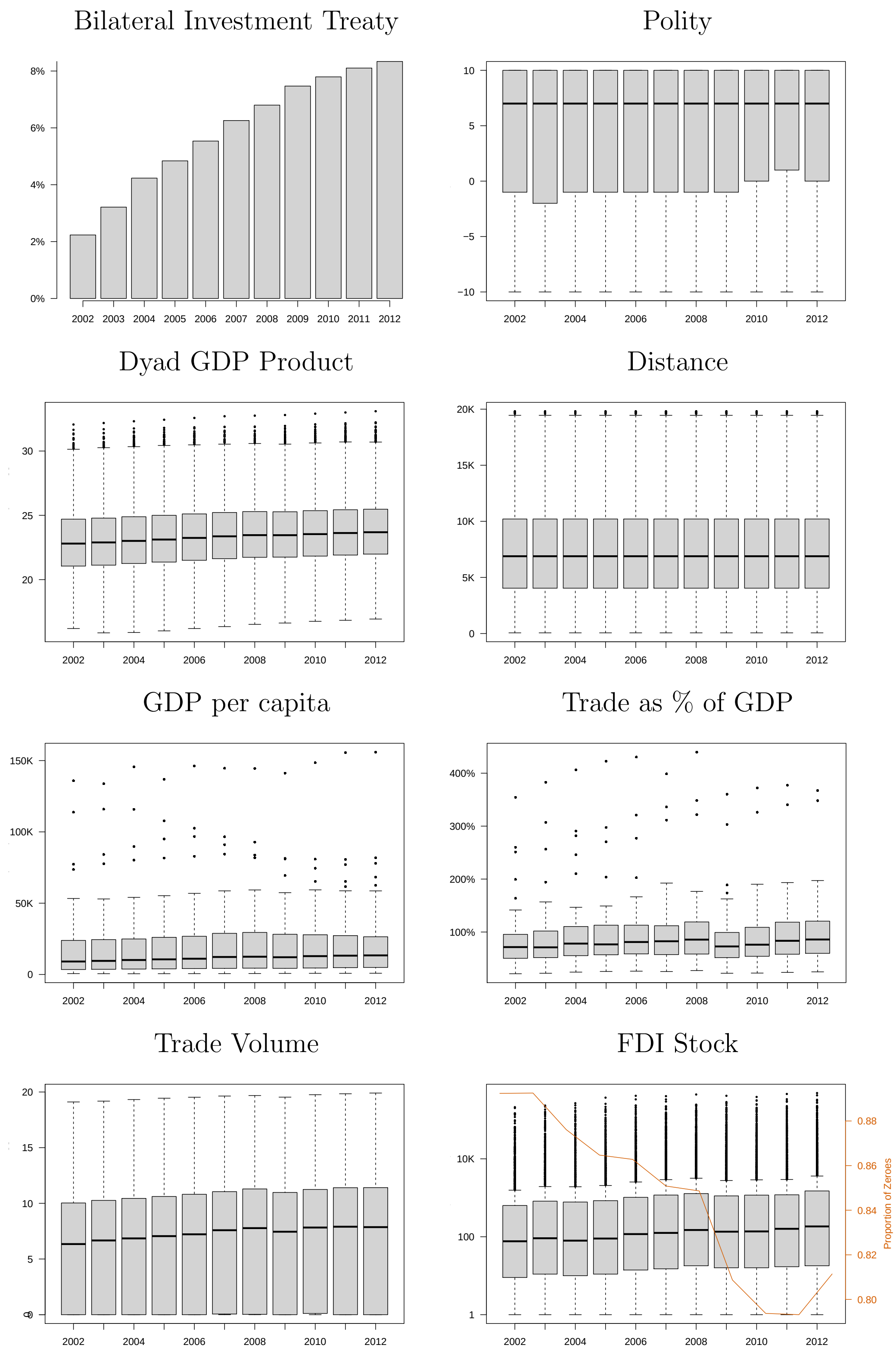

Figure 9: Summary Statistics.

Table 1: Correlation Matrix

	Mass	Distance, logged	Polity	Trade Openness	BIT
Mass	1	-0.003	0.091	-0.166	0.141
Distance, logged	-0.003	1	0.008	-0.057	-0.085
Polity	0.091	0.008	1	-0.078	0.018
Trade Openness	-0.166	-0.057	-0.078	1	0.032
BIT	0.141	-0.085	0.018	0.032	1
Trade Volume	0.714	-0.215	0.215	-0.055	0.143
GDP per capita, ln	0.392	-0.084	0.166	0.225	0.093
Alliance Treaty	0.133	-0.348	0.073	-0.044	0.021
Defense Treaty	0.065	-0.391	0.065	-0.046	0.010

Table 2: Correlation Matrix Continued

	Trade Volume	GDP per capita, ln	Alliance Treaty	Defense Treaty
Mass	0.714	0.392	0.133	0.065
Distance, logged	-0.215	-0.084	-0.348	-0.391
Polity	0.215	0.166	0.073	0.065
Trade Openness	-0.055	0.225	-0.044	-0.046
BIT	0.143	0.093	0.021	0.010
Trade Volume	1	0.330	0.216	0.177
GDP per capita, ln	0.330	1	0.098	0.038
Alliance Treaty	0.216	0.098	1	0.850
Defense Treaty	0.177	0.038	0.850	1

B Time-Pooled Model Results

In this paper, we estimate a separate model for each year from 2002 to 2012. Results in Figures xxx show significant heterogeneity in the estimates over time. For robustness checks, we re-estimate the count ERGM by pooling the data.

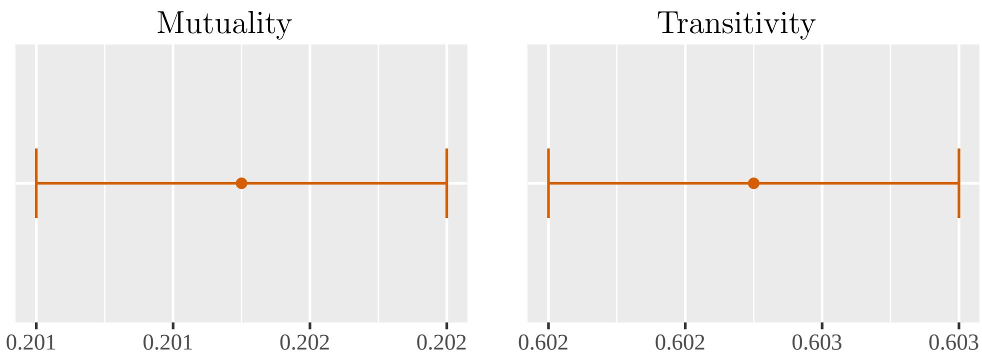

Figure 10: Estimates of Dependence terms in time-pooled ERGMs. Bars span 95% confidence intervals.

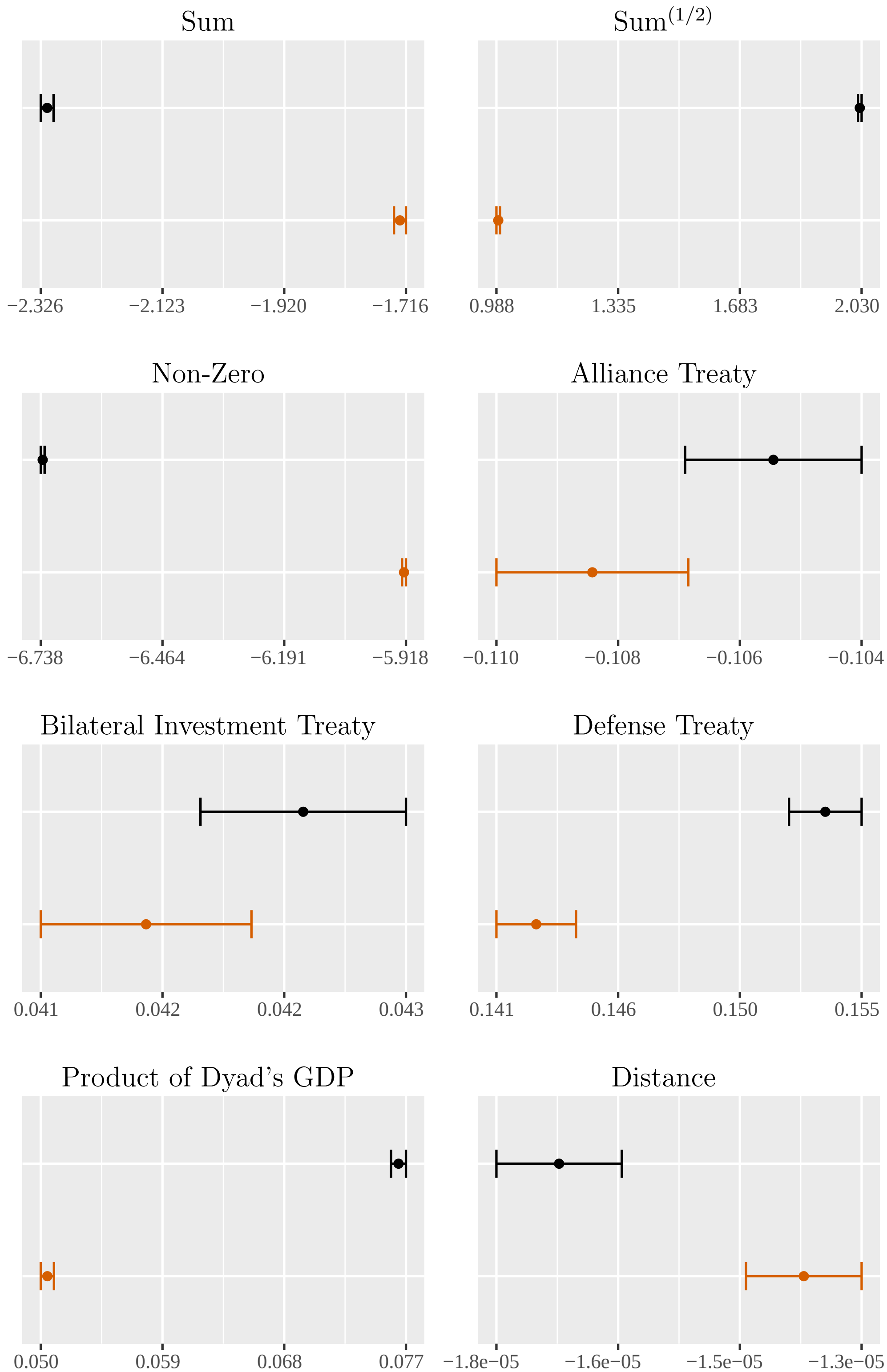

Figure 11: Estimates of terms in time-pooled ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).

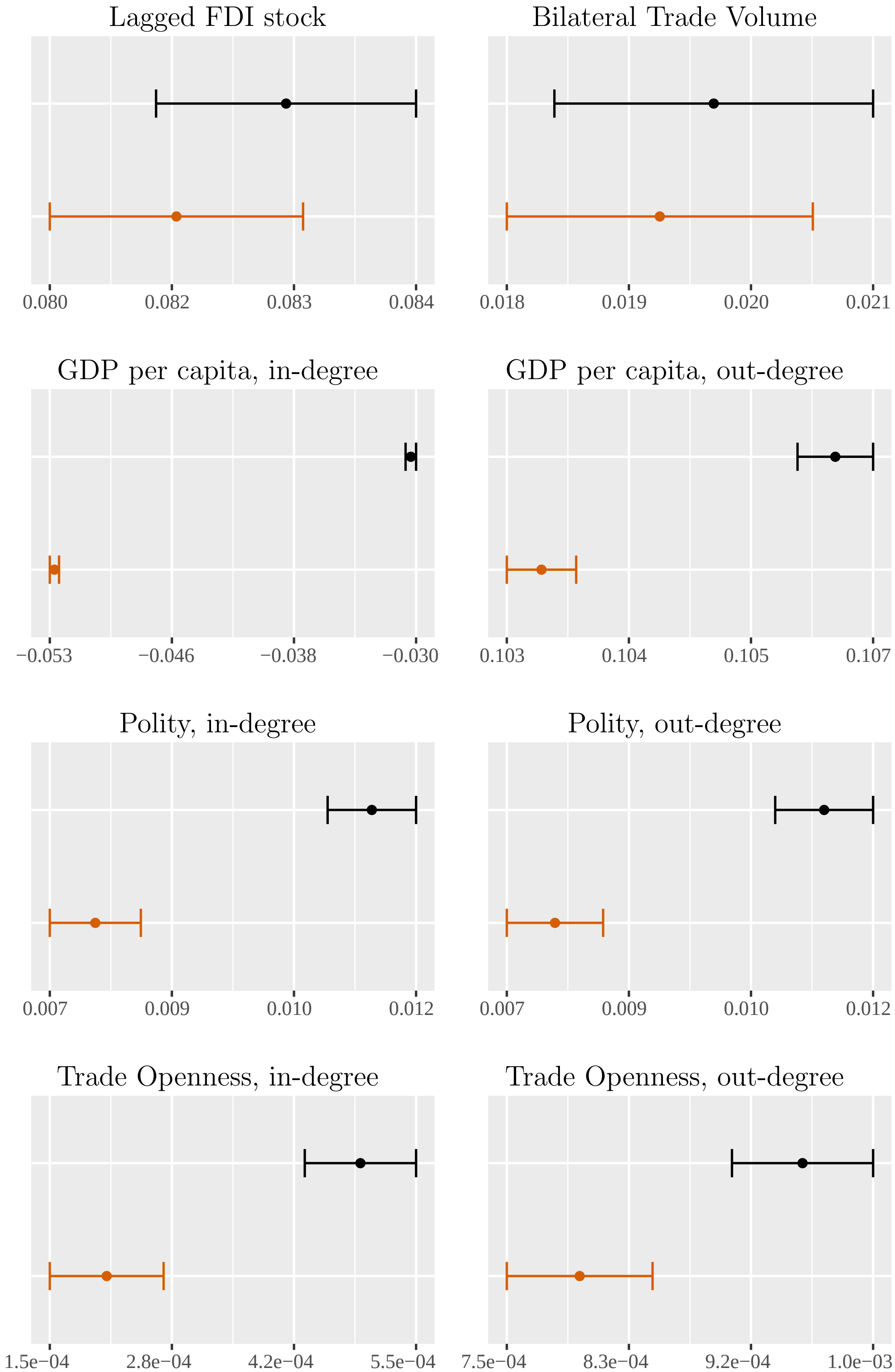

Figure 12: Estimates of terms in time-pooled ERGMs. Bars span 95% confidence intervals. Black coefficient representations are from models excluding dependence terms (i.e., transitivity and reciprocity).