Appendix

A Summary Statistics

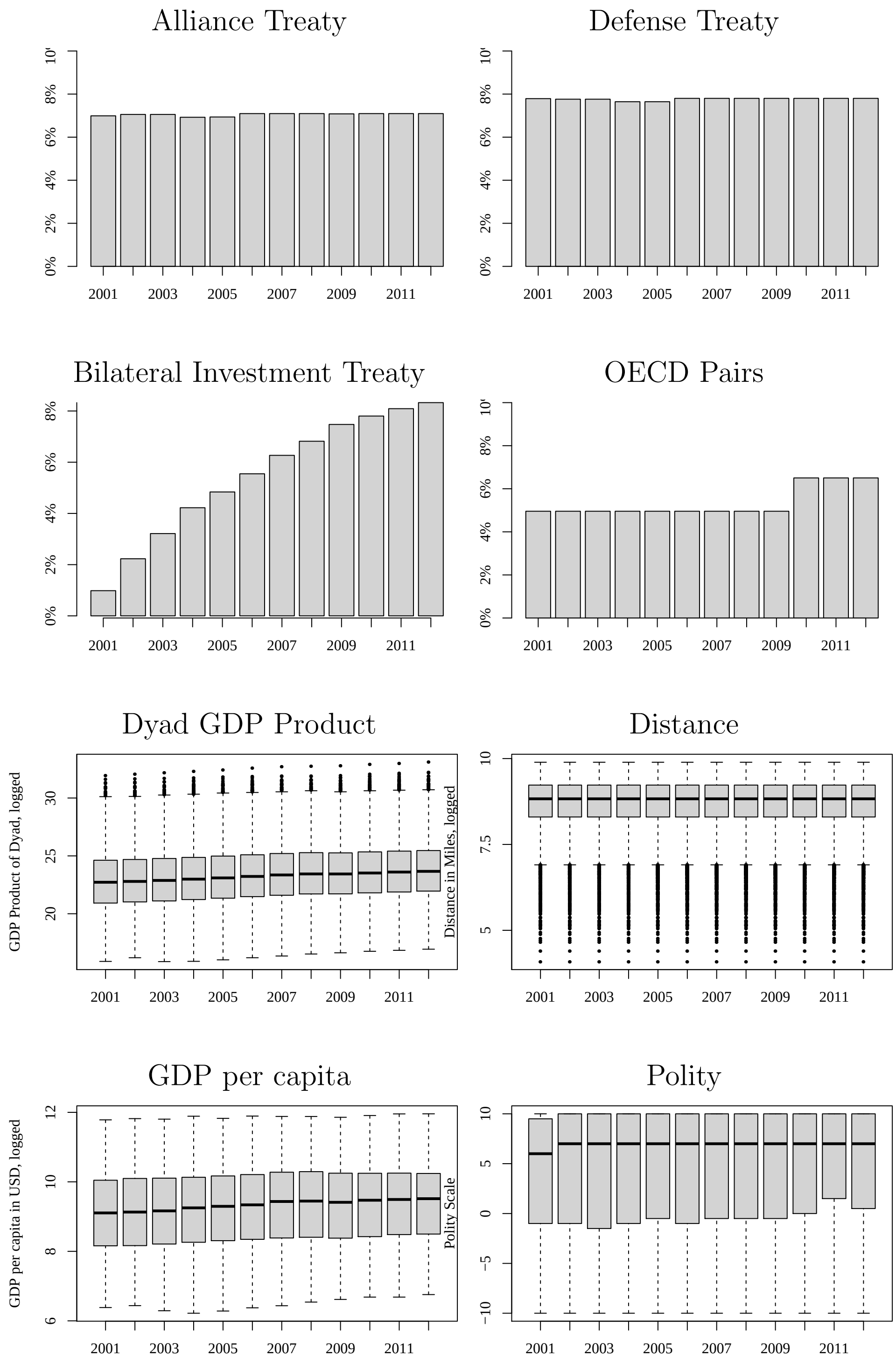
Table A: Correlation Matrix

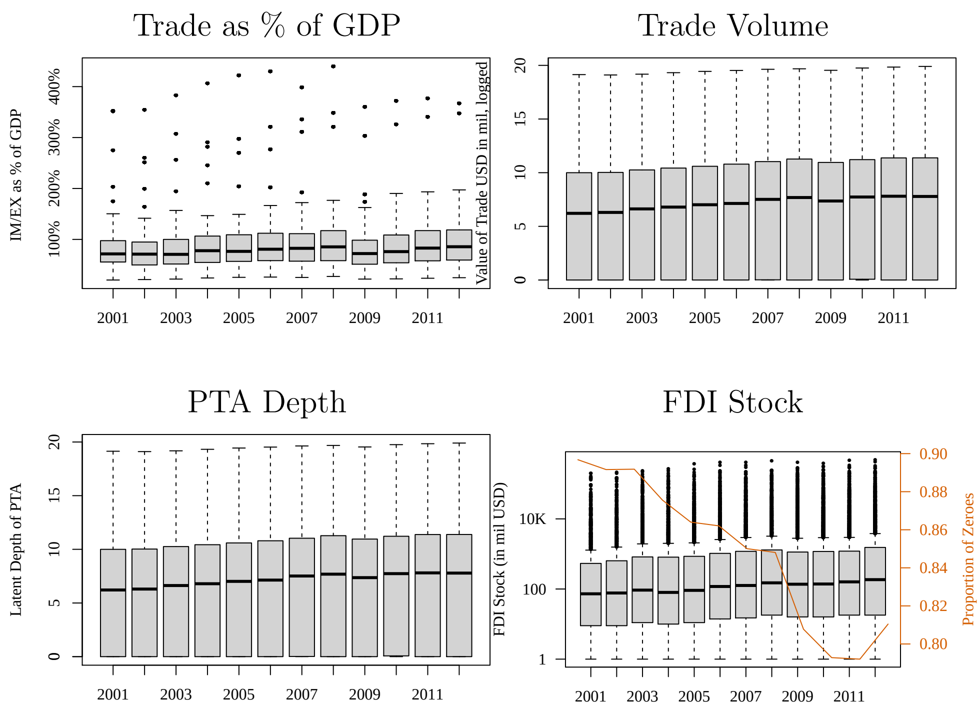
	Distance	Defense Treaty	Polity	Trade Openness
Distance	1			
Defense Treaty	-0.39****	1		
Polity	0.01****	0.06****	1	
Trade Openness	-0.06****	-0.04****	-0.07****	1
PTA Depth	-0.41****	0.19****	0.18****	0.06****
BIT	-0.08****	0.01****	0.02****	0.03****
Mass	0.00	0.07****	0.10****	-0.17****
Alliance Treaty	-0.35****	0.85****	0.07****	-0.04****
GDP pc	-0.08****	0.04****	0.16****	0.24****
Trade Volume	-0.22****	0.18****	0.23****	-0.06****
OECD pair	-0.23****	0.28****	0.20****	0.01****

	PTA Depth	BIT	Mass	Alliance Treaty
PTA Depth	1			
BIT	0.07****	1		
Mass	0.10****	0.14****	1	
Alliance Treaty	0.17****	0.02****	0.14****	1
GDP pc	0.15****	0.09****	0.40****	0.10****
Trade Volume	0.28****	0.14****	0.72****	0.22****
OECD pair	0.31****	-0.01****	0.29****	0.29****

	GDP pc	Trade Volume	OECD pair
GDP pc	1		
Trade Volume	0.34****	1	
OECD pair	0.23****	0.34****	1

Table B: Frequency count bar-plots for binary variables and distribution plots for continuous variables.





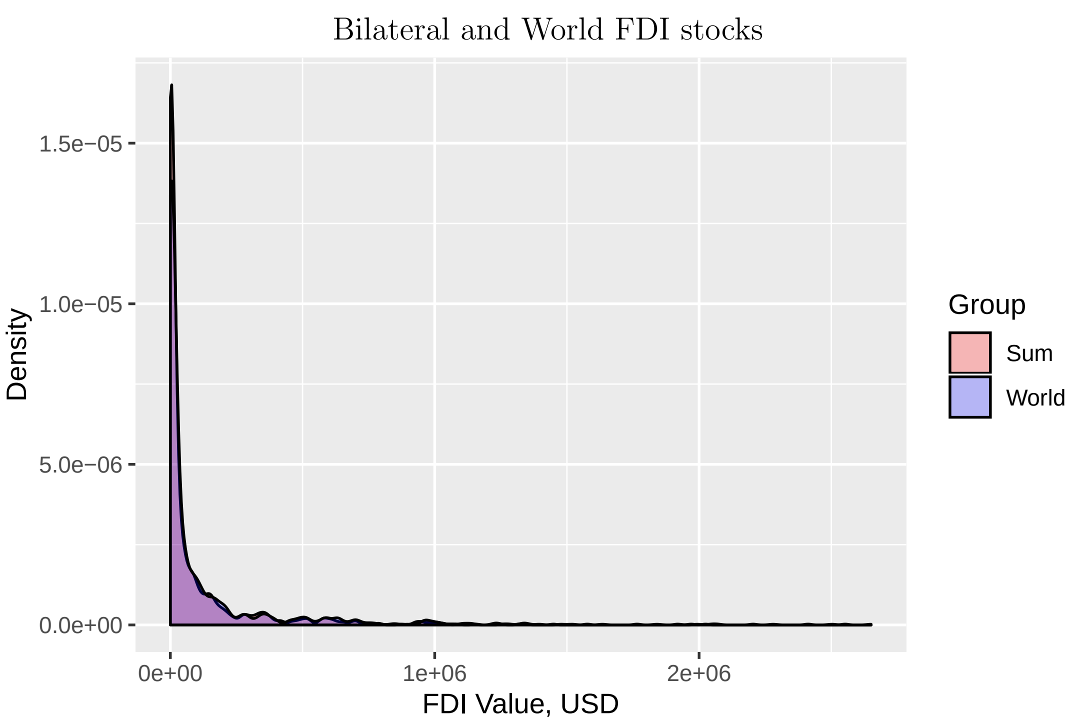


Figure A: Density Plot of Reported World FDI Stocks and Summed Bilateral FDI Stocks.

B Model and Variable Discussion

Model Justification

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

Correlations Before and After Rounding FDI

In this section we also investigate whether the structure of associations between FDI an the dyadic covariates included in the count ERGM is significantly changed by rounding the natural logarithm of FDI. In Table C we present the correlation between the dyadic variables included in our ERGMs, and the pre-rounded log-FDI. In Table D we present the correlation between the dyadic variables and the rounded version log-FDI. In Table E we present two-tailed p-values from tests, developed by Dunn and Clark (1969) and implemented in the `R` package `psych` (Revelle, 2018), of the null hypothesis that the correlations pre and post-rounding are equal. The lowest p-value is 0.12, and the majority are greater than 0.50, indicating that rounding log-FDI to create a count variable does not significantly change the structure of associations in the data.

	Lag FDI	GDP prod	Dist	Alliance	Defense	Trade	BIT	Both OECD	PTA
2002	0.37	0.38	-0.24	0.24	0.22	0.41	0.01	0.51	0.22
2003	0.39	0.37	-0.25	0.24	0.22	0.41	0.01	0.53	0.24
2004	0.40	0.37	-0.26	0.25	0.22	0.42	0.02	0.52	0.25
2005	0.39	0.40	-0.26	0.26	0.23	0.44	0.03	0.50	0.24
2006	0.37	0.38	-0.27	0.25	0.22	0.44	0.03	0.50	0.26
2007	0.36	0.39	-0.28	0.26	0.23	0.45	0.04	0.50	0.31
2008	0.39	0.40	-0.29	0.26	0.23	0.44	0.04	0.50	0.30
2009	0.37	0.43	-0.31	0.28	0.25	0.48	0.07	0.49	0.31
2010	0.38	0.46	-0.30	0.28	0.25	0.49	0.08	0.45	0.30
2011	0.39	0.45	-0.30	0.28	0.25	0.49	0.08	0.44	0.30
2012	0.38	0.44	-0.27	0.26	0.24	0.45	0.06	0.45	0.25

Table C: Correlation between dyadic variables and FDI

Correlation between dyadic variables and rounded FDI

	Lag FDI	GDP prod	Dist	Alliance	Defense	Trade	BIT	Both OECD	PTA
2002	0.36	0.38	-0.24	0.24	0.21	0.40	0.01	0.51	0.22
2003	0.39	0.37	-0.25	0.24	0.22	0.41	0.01	0.52	0.24
2004	0.40	0.37	-0.26	0.25	0.22	0.42	0.02	0.52	0.25
2005	0.39	0.39	-0.26	0.26	0.23	0.44	0.03	0.50	0.24
2006	0.36	0.38	-0.27	0.25	0.22	0.44	0.03	0.50	0.26
2007	0.36	0.39	-0.28	0.26	0.23	0.44	0.04	0.50	0.30
2008	0.38	0.40	-0.29	0.25	0.23	0.44	0.04	0.50	0.30
2009	0.36	0.43	-0.31	0.28	0.25	0.47	0.07	0.49	0.31
2010	0.37	0.46	-0.30	0.28	0.25	0.49	0.08	0.45	0.30
2011	0.39	0.44	-0.29	0.28	0.25	0.48	0.08	0.44	0.30
2012	0.38	0.44	-0.26	0.26	0.24	0.45	0.06	0.44	0.25

Table D: Correlation between dyadic variables and FDI

Two-tailed p-value in test for difference in correlations before and after rounding

	Lag FDI	GDP prod	Dist	Alliance	Defense	Trade	BIT	Both OECD	PTA
2002	0.24	0.57	0.72	0.65	0.69	0.58	1.00	0.47	0.88
2003	0.12	0.69	0.78	0.84	0.81	0.66	0.91	0.64	0.86
2004	0.22	0.69	0.66	0.75	0.72	0.57	0.91	0.51	0.75
2005	0.18	0.57	0.74	0.76	0.76	0.57	0.98	0.47	0.99
2006	0.18	0.68	0.77	0.76	0.75	0.65	0.95	0.43	0.96
2007	0.15	0.75	0.81	0.89	0.81	0.82	0.93	0.51	0.78
2008	0.19	0.73	0.71	0.86	0.89	0.73	0.98	0.52	0.84
2009	0.20	0.66	0.73	0.83	0.79	0.60	0.99	0.33	0.80
2010	0.20	0.71	0.82	0.90	0.91	0.68	1.00	0.52	0.96
2011	0.20	0.64	0.72	0.85	0.82	0.71	0.88	0.51	0.95
2012	0.23	0.72	0.73	0.84	0.88	0.76	0.87	0.55	0.92

Table E: Correlation between dyadic variables and FDI

Model Fit

To further investigate how the network model fits better than a model assumes unit independence, we compare simulated networks from the two models to the observed networks along four dimensions and for each year—a standard approach to evaluating the goodness of fit of network models (Hunter, Goodreau and Handcock, 2008). We present quantities that evaluate the fit of the models to the reciprocity, transitivity, sender heterogeneity, and receiver heterogeneity of the networks. To measure the fit of the reciprocity, we use the weighted reciprocity measure proposed by Garlaschelli and Loffredo (2004)—the correlation between the weights of edges within the same dyads. This measure ranges between -1 and 1, with higher values corresponding to a greater degree of reciprocity. The measure we use to measure weighted transitivity comes from Opsahl and Panzarasa (2009)—the ratio of total transitive triple weights to total two-path weights, where the weight of a configuration is defined as the minimum value within the configuration. This measure ranges between 0 and 1, with larger values corresponding to more transitive network. To measure receiver and sender heterogeneity, we follow Minhas, Hoff and Ward (2019) and consider the variance (presented as standard deviations) in the total received (i.e., indegree) and total sent (i.e., outdegree) by each node.

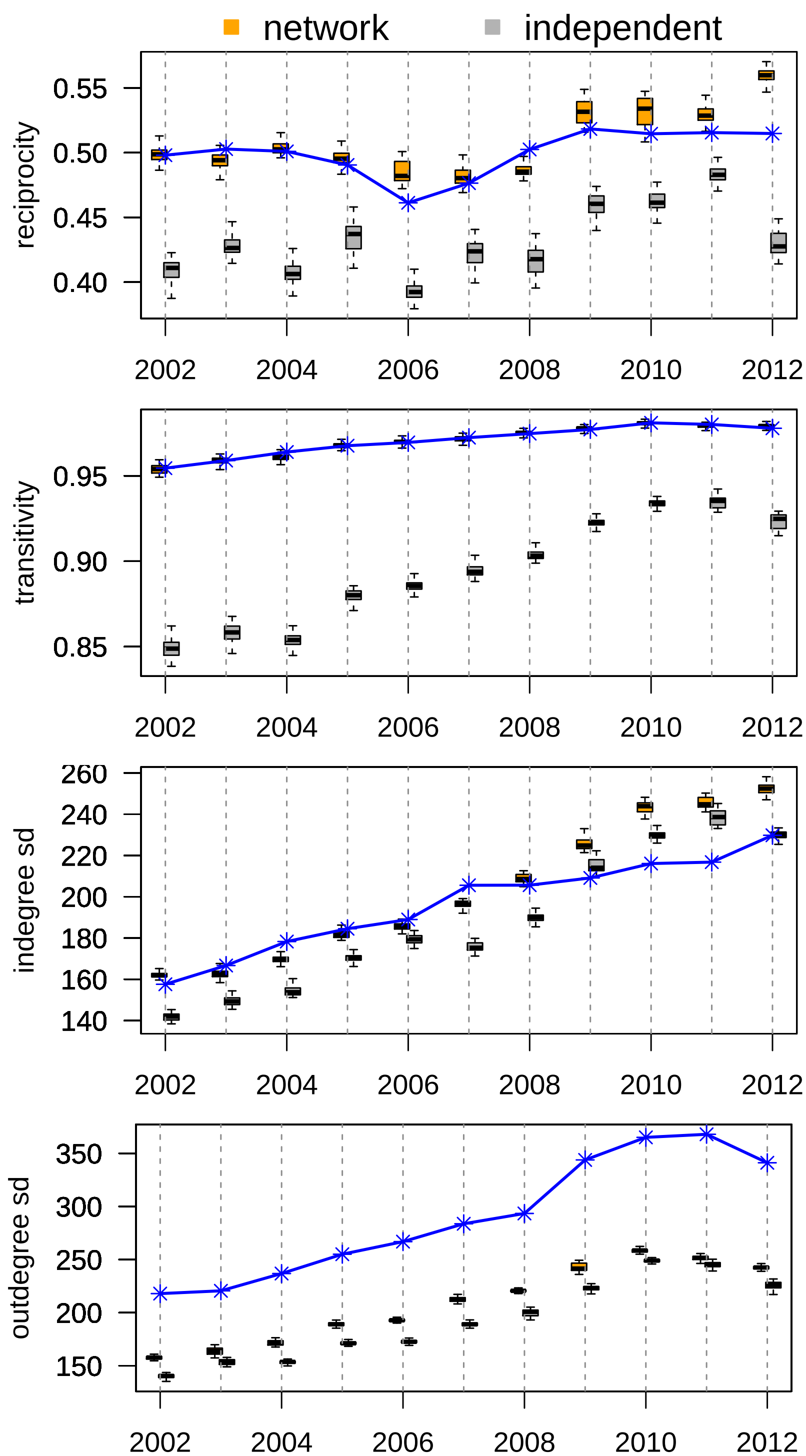


Figure B: Structural fit of the network and independence models. Boxplots depict distributions over 100 simulated networks. The orange boxplots (those to the left of the dashed vertical lines), depict distributions from the full network model. The gray boxplots depict distributions from the independence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

We see in Figure B that the network model provides a much better fit to the observed network than does the independent model. The boxplots depict the network statistics computed on 100 networks simulated from each model in each year. The network model fits the reciprocity and transitivity in the observed network quite well, and consistently better than does the independence model. The network model generally fits the indegree standard deviation well, but in some years the independent model provides a better fit. The one statistic that is not fit very well with either model is the outdegree standard deviation. Unfortunately, the specifications available for modeling the degree distributions in the count ERGM are still rather limited. The two statistics currently available to model degree heterogeneity—the covariance and square-root-covariance of edge values sent or received by the same node, exhibited degeneracy when fit to the FDI networks. The development of less degeneracy-prone degree statistics, such as the geometrically weighted degree terms available for binary ERGMs (Snijders, Pattison, Robins and Handcock, 2006), is an important avenue for future research with the count ERGM.

C 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 all network dependence terms are significant in the time-pooled models. Non-OECD pairs exhibit less reciprocity than OECD pairs, but the average effect for the time sample is still positive and significant.

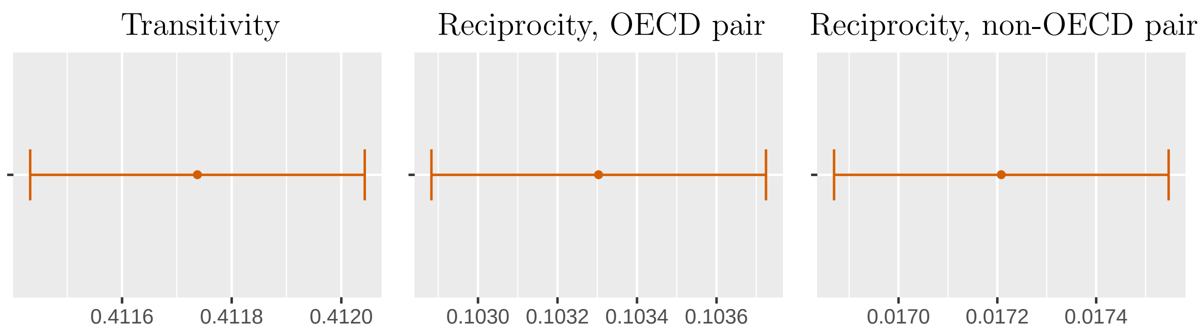


Figure C: Estimates of network terms in time-pooled ERGMs. Bars span 95% confidence intervals.

D AME Model Results

As mentioned in the discussion of the GOF statistics of the main model, the count ERGM does not fit out degree actor heterogeneity very well. At the end of the day, there's no model in existence that can account for all of the peculiarities of this data (zero inflation, reciprocity, transitivity, actor heterogeneity). A relatively new latent space model called AMEN has been developed and, unlike older versions of the LSM, includes terms that can be used to account for reciprocity and transitivity (Minhas, Hoff and Ward, 2019). It is also effective at accounting for actor heterogeneity, though not for zero-inflation and is not able to condition reciprocity as the ERGM does. We replicate our main model with this new model to assure that our results regarding transitivity and reciprocity are robust to accounting for actor heterogeneity. These results are estimated with the R package `amen` (Hoff, Fosdick, Volfovsky and He, 2017) using un-transformed FDI stock values and a

Gaussian edge distribution. Below the results in Figure D show that both transitivity and reciprocity are significant even when better accounting for actor heterogeneity.

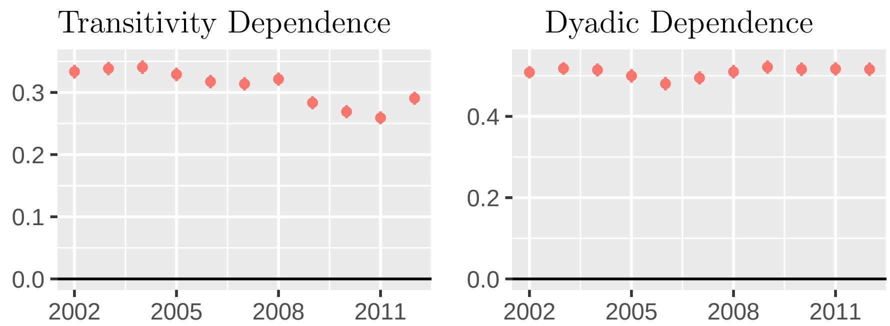


Figure D: Dependence patterns. Bars span 95% confidence intervals.

E Subset by Missingness Results

The bilateral FDI data are collected mainly from national sources with technical assistance from UNCTAD; in cases where data are not available from host countries, UNCTAD uses data from partner countries (mirror data) as well as from other international organizations.[1] One challenge of using bilateral FDI data is the large number of unreported values. The missing values seem likely to be zero or a negligible amount (and thus not truly missing, but unreported because there was nothing to report). Comparing a country's total FDI to the sum of bilateral FDI for each year, we find that in most cases the difference is small and likely due to rounding, centering around zero (see Figure A in Appendix A). Therefore, for our main models we impute the missing values with zeros so that we have a complete data set to model network dependence. In section E of this Appendix, we present results using an alternative approach—subsetting to sets of countries on which we have more complete data, a common approach in dyadic research in political economy (e.g., Cao and Ward, 2014; Pettersson and Johansson, 2013). Our main findings regarding the effects of transitivity and reciprocity are robust to this alternative approach.

In the paper, we imputed missing values with zeros. In this section, we check whether our results are robust if we analyze a subset of the data set based on the level of missingness. To subset the data, we approximate total level of missingness in the adjacency matrices (q) by using the proportion of missing values for each node (p). We conduct two robustness checks: (1) when $p = 0.86$, $q \approx 0.50$ and $n = 70$; and (2) when $p = 0.72$, $q \approx 0.25$ and $n = 28$. In the first case, we only include nodes with missing values that are 86% or less of the possible edges for the entire data set, which leaves us with an adjacency matrix that is only missing 50% of the values (70 countries in total). Similarly, the second set only includes nodes with missing values that are 72% or less of the possible edges for the entire dataset, which leaves us with an adjacency matrix that is only missing 25% of the values (28 countries in total).

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

Following our approach in the paper, we impute missing values in the two subsets of the data with zeros.

Figures E and F present the results for the two robustness checks, respectively. We see that FDI networks show strong transitivity for all years. Reciprocity effects for OECD pairs are more erratic but still significant. Reciprocity effects for non-OECD pairs follow the same pattern of starting negative and gradually becoming positive. The erratic coefficients for OECD pairs may be because the subset has substantial two-way FDI flows and thus there is little variation in the level of reciprocity.

q ≈ 0.50

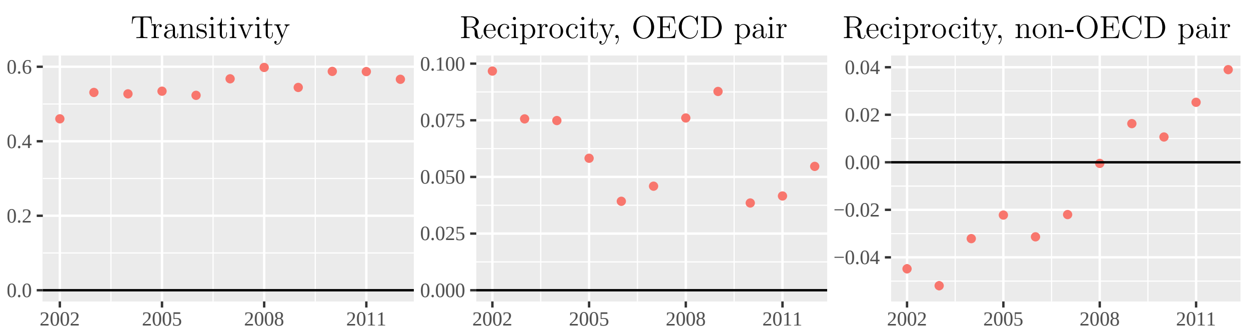


Figure E: Estimates of Dependence terms. Bars span 95% confidence intervals.

q ≈ 0.25

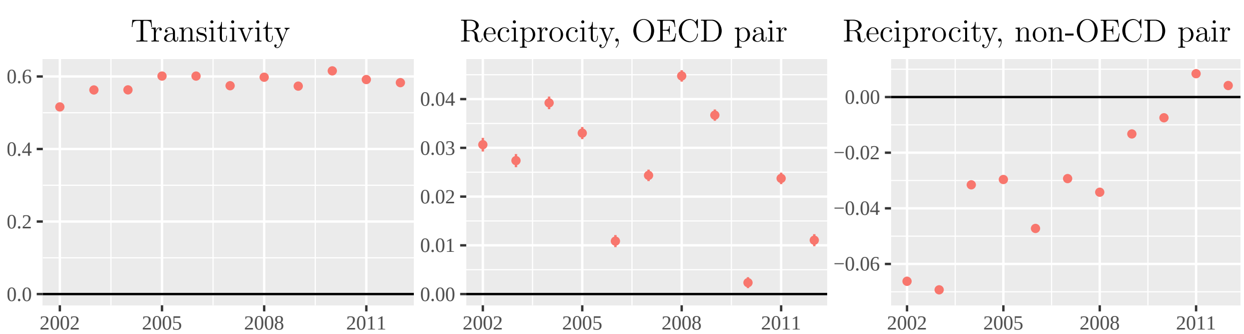


Figure F: Estimates of Dependence terms. Bars span 95% confidence intervals.

F Tax Incentives and FDI

One potential concern with bilateral FDI data is that they include round-tripping FDI, in which domestic firms transfer funds to a foreign country (typically a tax haven) and invest back as "foreign capital" to take advantage of preferential policies that their home countries offer to foreign investors (Borga, 2016). Round-tripping FDI could inflate reciprocity. Further, firms may use tax havens to channel funds to other countries (Sauvant, 2017). If firms in one country use a tax haven to invest in another country whose firms also invest in the former country, it creates an artificial triangle closure of investment flows (i.e., transitivity). To address these issues in bilateral FDI data and check the robustness of our findings, we re-estimated the model by including the corporate tax rate for both the sending and receiving country[2] and estimating models that exclude tax havens. The countries dropped as tax havens are Namibia, Trinidad and Tobago, Bahrain, Luxembourg, the United Kingdom, Ireland, and the Netherlands. We used the EU list of 17 countries as a base list, although most of them were not in our sample due to data availability.[3] We also added Luxembourg, the United Kingdom, Ireland, and the Netherlands since they are often considered cooperative tax havens.[4] Figure G plots the results for reciprocity and transitivity for the models with corporate tax rates. We see that the results on reciprocity become a little weaker when tax rates are included, but they remain significant in most years. Including tax rates does not affect transitivity. Figure H plots the results for reciprocity and transitivity for the models that exclude tax havens and the results are nearly identical the main results in the paper.

[2]Corporate tax rate data comes from the World Bank's *World Development Indicators*.

[3]https://ec.europa.eu/taxation_customs/tax-common-eu-list_en

[4]Matthew C. Klein. "What the Foreign Direct Investment Data Tell Us About Corporate Tax Avoidance." *Financial Times*, November 23, 2017. https://ftalphaville.ft.com/2017/11/23/2196028/what-the-foreign-direct-investment-data-tell-us-about-corporate-tax-avoidance/

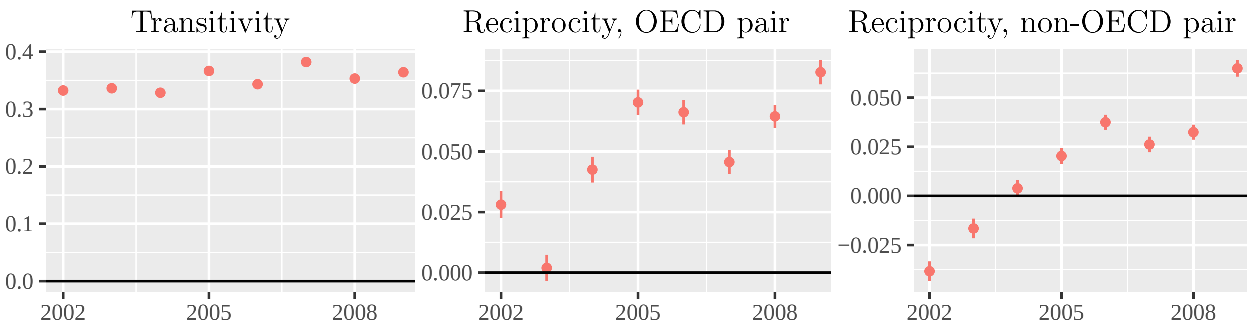


Figure G: Estimates of Dependence terms for models with corporate tax rates. Bars span 95% confidence intervals.

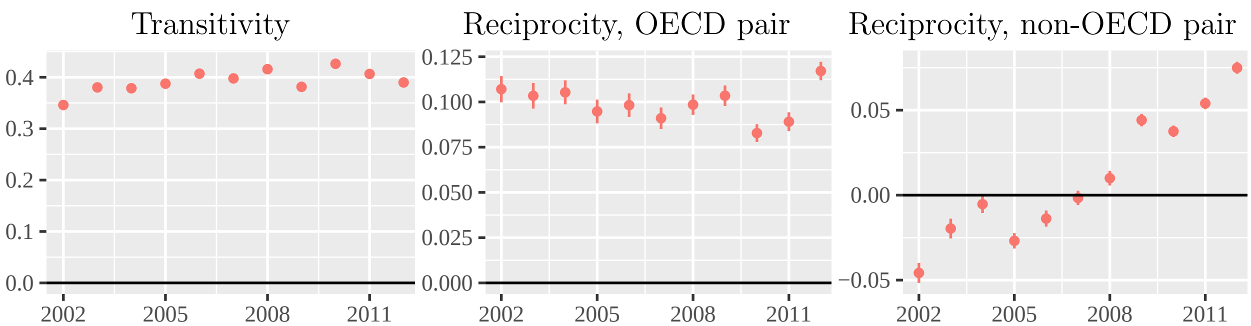


Figure H: Estimates of Dependence terms for models without tax havens. Bars span 95% confidence intervals.

G Excluding the European Union

A significant portion of the FDI in the global economy involves the European Union and the majority of the top partners for the EU are other EU countries. This is because of proximity, similar business environments and endowments, and few barriers for EU firms to send FDI to other EU countries. Because of this, there is a high degree of clustering within the EU, and so we run models that drop all EU countries to test if reciprocity and transitivity is still significant for the rest of the global economy. We find that the transitivity statistic remains largely unchanged after dropping EU countries and that reciprocity is also similar to the main results, but slightly lower and less stable.

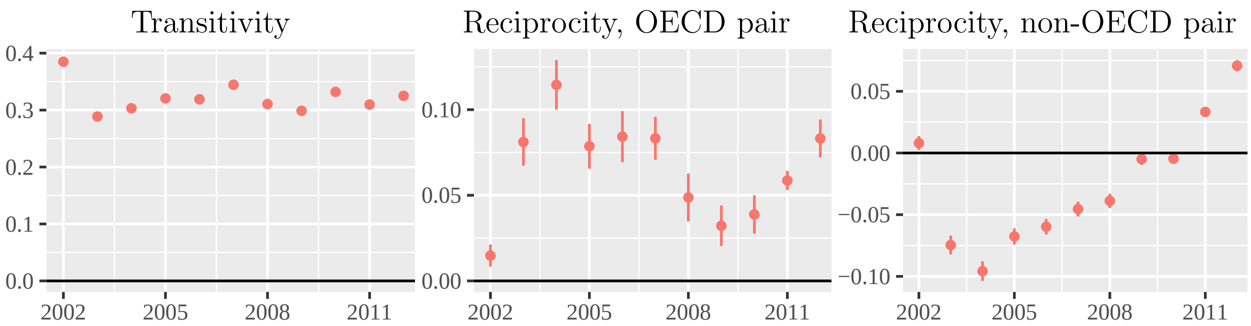


Figure I: Estimates of Dependence terms. Bars span 95% confidence intervals.

H Exchange rates and Inflation

FDI stocks can vary year to year due to reasons unrelated to FDI flows, such as revaluation. While it is impossible to perfectly address this limitation of the data, we add origin and destination node level inflation and exchange rate variables to our main models to control for this. The results for transitivity remain positive and significant, but slightly lower. Reciprocity also drops for both OECD and non-OECD pairs, even becoming negative in 2007 for OECD pairs, but remains positive and significant for most years for OECD pairs and non-OECD pairs still pattern convergence by the end of the time sample.

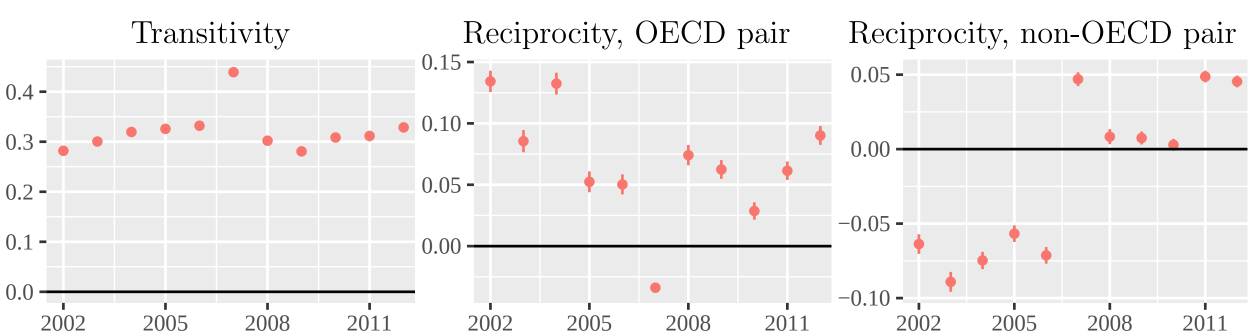


Figure J: Estimates of Dependence terms. Bars span 95% confidence intervals.

I Ripple Effect Simulation

We investigate the interdependence in the FDI network by simulating networks after edge elimation from the full model estimated for 2012.[5] The complete elimination of a single FDI edge would be admittedly unlikely, 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).

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.[6]

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

[5]Our conclusions are robust to using other years—we use 2012 for consistency with the model interpretations presented in the paper.

[6]Note that despite including the total amount of investment in the network (via Sum : $\boldsymbol{g(y)}$), the ERGM does not fix the sum of edges in the network—it simply generates networks with, on average, the same value of Sum : $\boldsymbol{g(y)}$ as seen in the observed network. As such, eliminating a single edge from the network will have virtually no effect on the expected values of other edges.

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

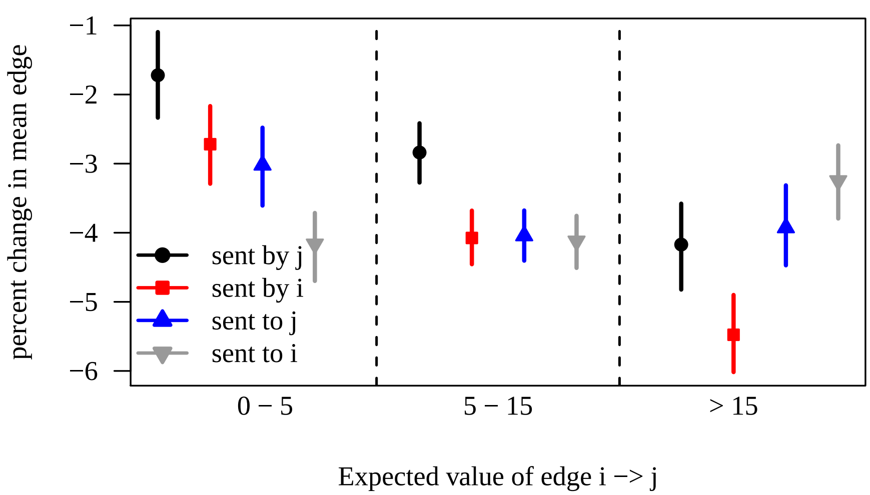


Figure K: Results from simulation exercise investigating the effects of eliminating edge $i \rightarrow j$. Points are drawn at the average values over all edges in the 2012 network. The bars span 95% confidence intervals.

J Covariate interpretation

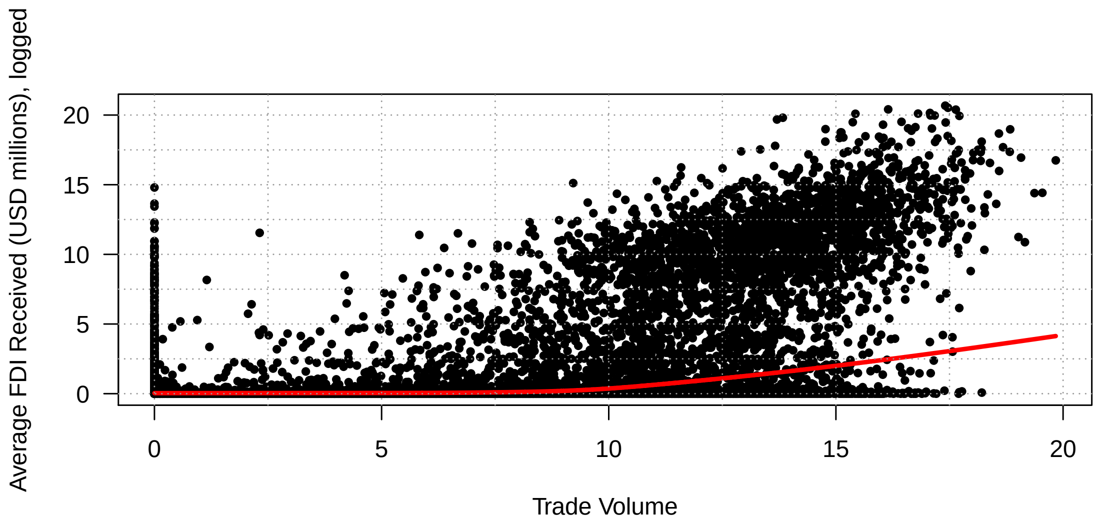


Figure L: Results from the simulation exercise investigating the effects of bilateral trade volume for year 2011. These results are from 500 simulations. The line in red is the Loess curve.

For the Poisson-reference ERGM these covariate estimates are usually interpreted by exponentiating Euler's constant to the power of the coefficient times the number of unit changes in the covariate to get the expected change in the tie weight (Krivitsky and Butts, 2013). Taking bilateral trade volume for example, if the FDI origin sent had a value of 10 logged units of trade, we would expect the value of logged FDI being sent to be 10.17 times more than if the trade volume was zero. Another method for interpreting covariate terms in the model is to simulate networks using the estimated coefficients while fixing all other covariate terms at the mean value and then comparing changes in the average edge value to the range of values of the covariate. For illustrative purpose, we present a plot of this for bilateral trade volume below in Figure L. Here the plot shows that as the trade volume increases from zero to 10 logged units there is a slow increase in the average level of FDI received, but increases after 10 logged units show a much sharper increase.

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