Appendix

A Summary Statistics

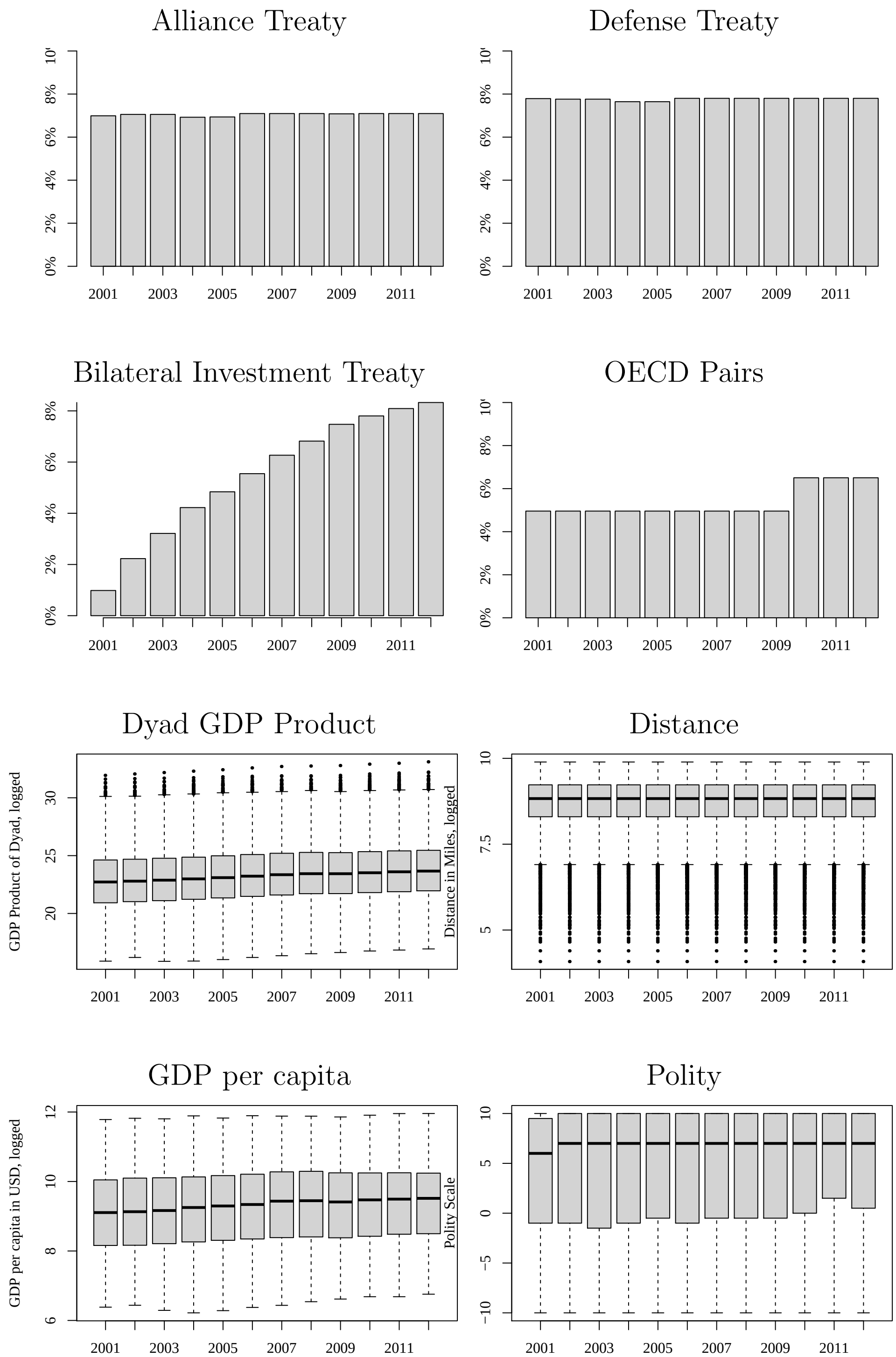
Table A: Correlation Matrix

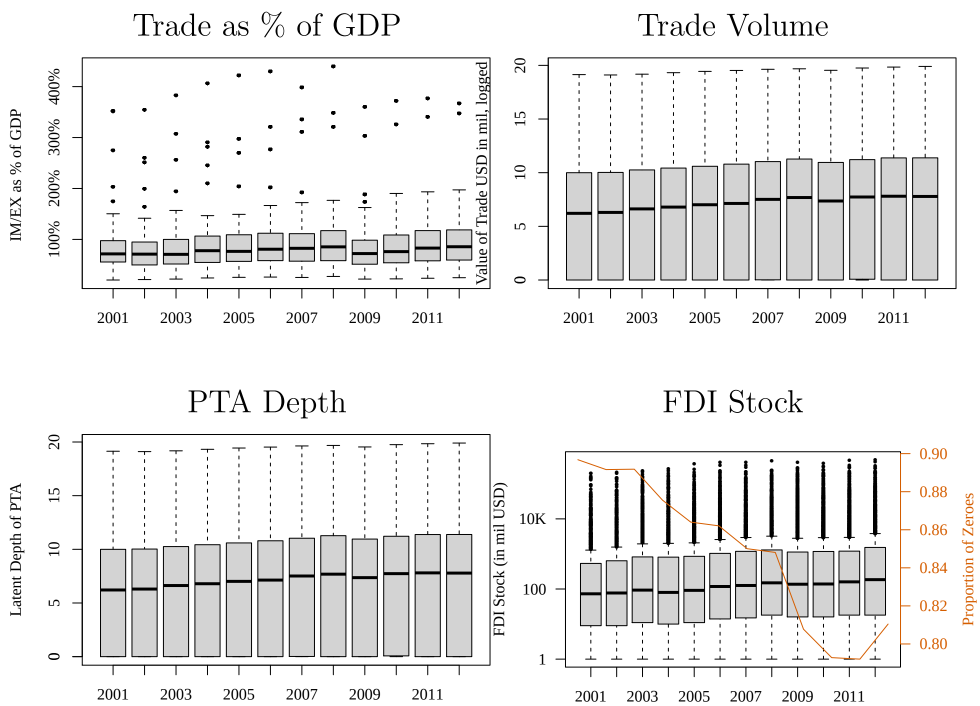
	Distance	Defense Treaty	Polity	Trade Openness
Distance	1			
Defense Treaty	-0.39****	1		
Polity	0.01****	0.06****	1	
Trade Openness	-0.06****	-0.04****	-0.07****	1
PTA Depth	-0.41****	0.19****	0.18****	0.06****
BIT	-0.08****	0.01****	0.02****	0.03****
Mass	0.00	0.07****	0.10****	-0.17****
Alliance Treaty	-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.





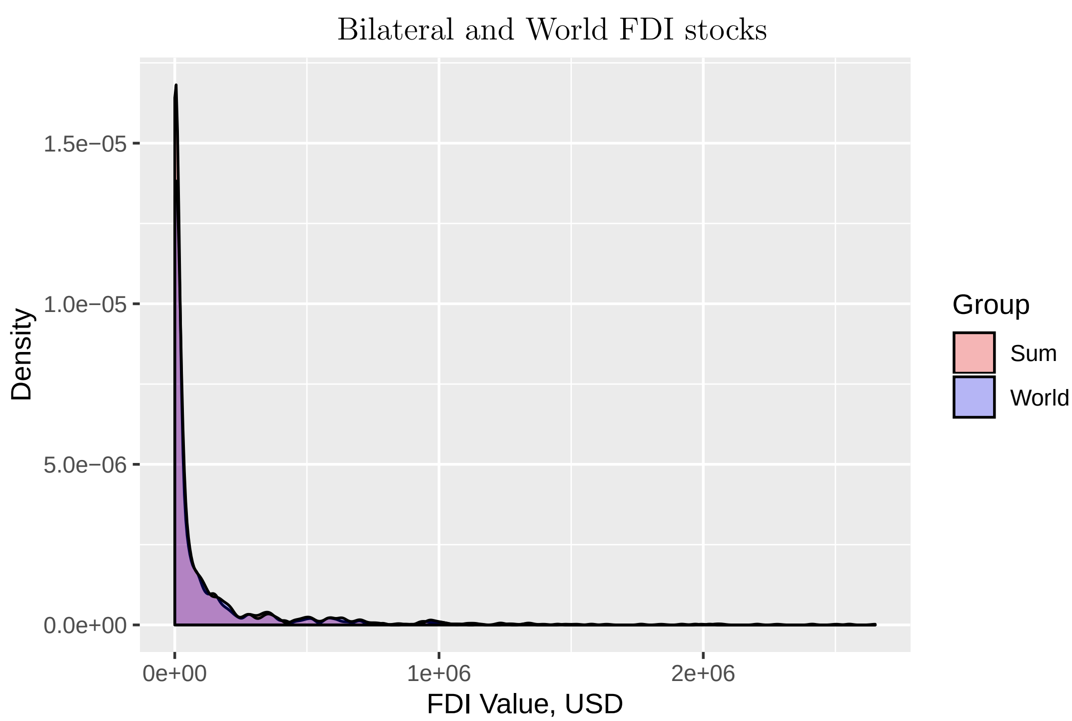


Figure A: Density Plot of Reported World FDI Stocks and Summed Bilateral FDI Stocks.

B Correlations Before and After Rounding FDI

In this section we 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

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 B 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.

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

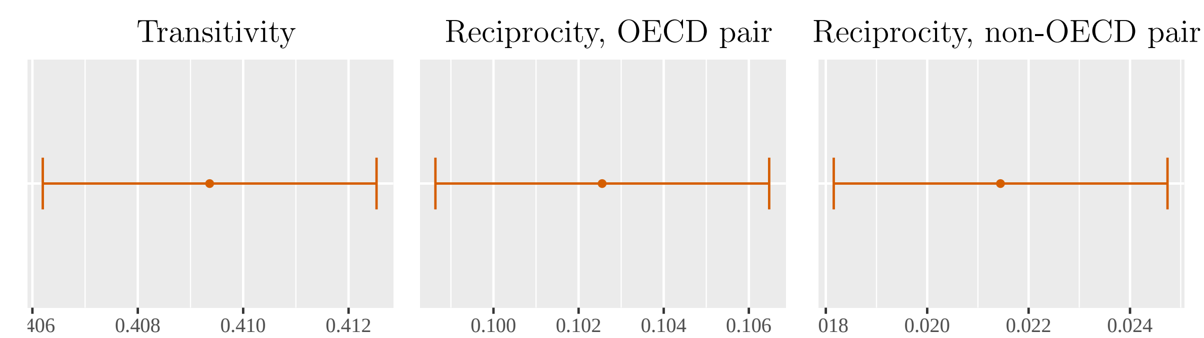


Figure B: Estimates of network terms in time-pooled ERGMs. Bars span 95% confidence intervals.

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

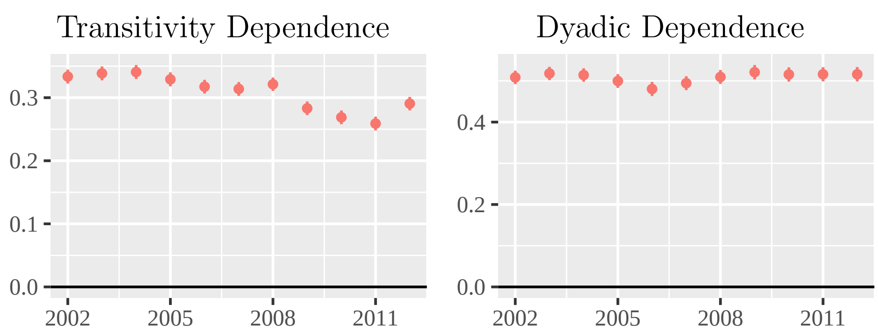


Figure C: Dependence patterns. Bars span 95% confidence intervals.

E Subset by Missingness Results

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

Figures D and E 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.

E.1 q ≈ 0.50

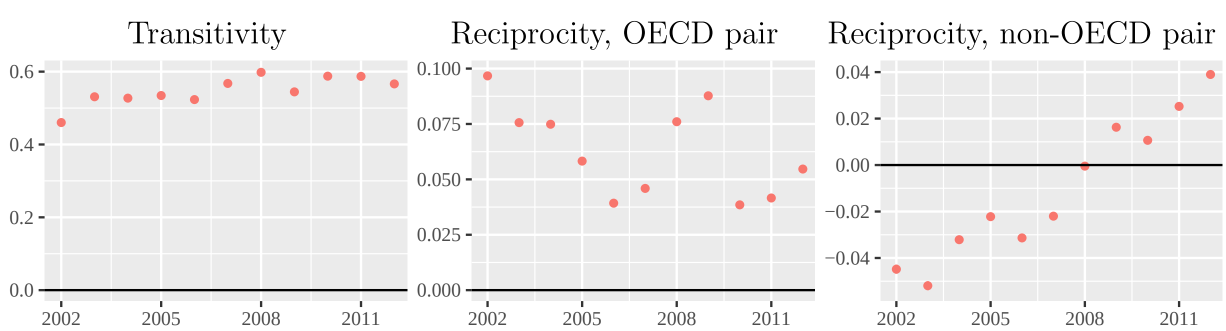


Figure D: Estimates of Dependence terms. Bars span 95% confidence intervals.

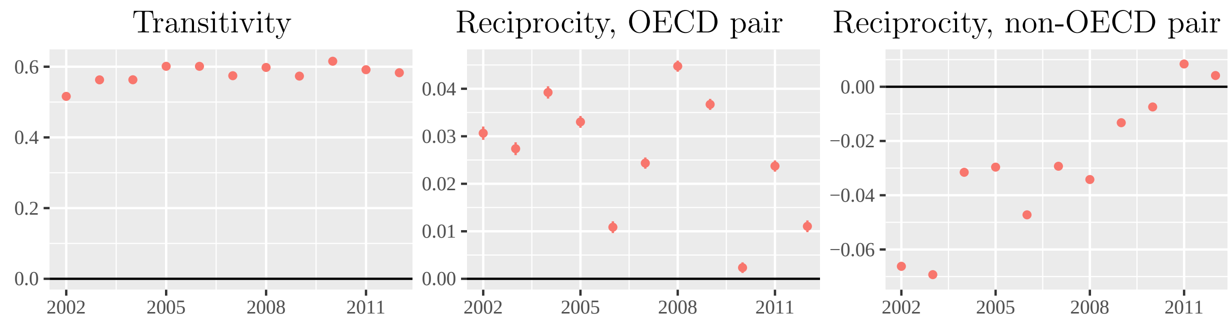


Figure E: Estimates of Dependence terms. Bars span 95% confidence intervals.

E.2 q $\approx$ 0.25

E.3 Multiple Imputations

In addition to subsetting by missingness, we also employ multiple imputations using the `R` package `Amelia`. For the imputations, we used the dataset that included all covariates and imputed the column for the original FDI stock values and then transformed the data for the models. We used ten imputations, modeled each imputed dataset and then combined the parameter estimates using standard Rubin's rules.

WILL ADD FIGURE ONCE MODELS FINISH

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[1] 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.[2] We also added Luxembourg, the United Kingdom, Ireland, and the Netherlands since they are often considered cooperative tax havens.[3] Figure F 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 G 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.

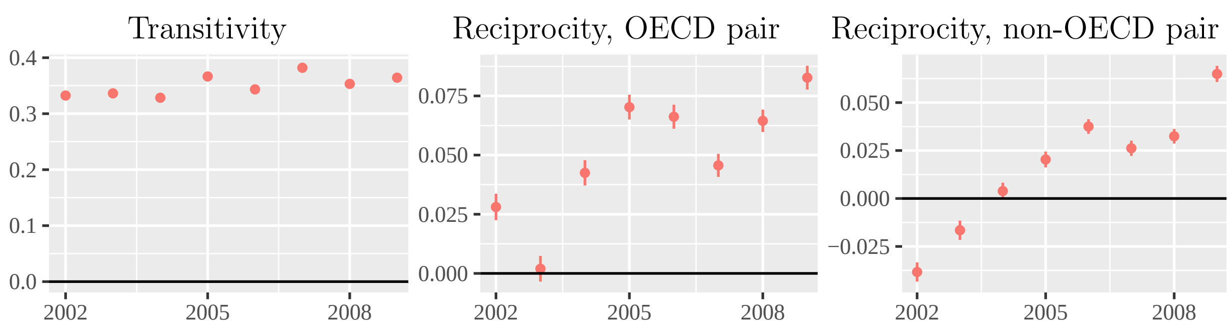


Figure F: Estimates of Dependence terms for models with corporate tax rates. Bars span 95% confidence intervals.

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

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

[3] 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/

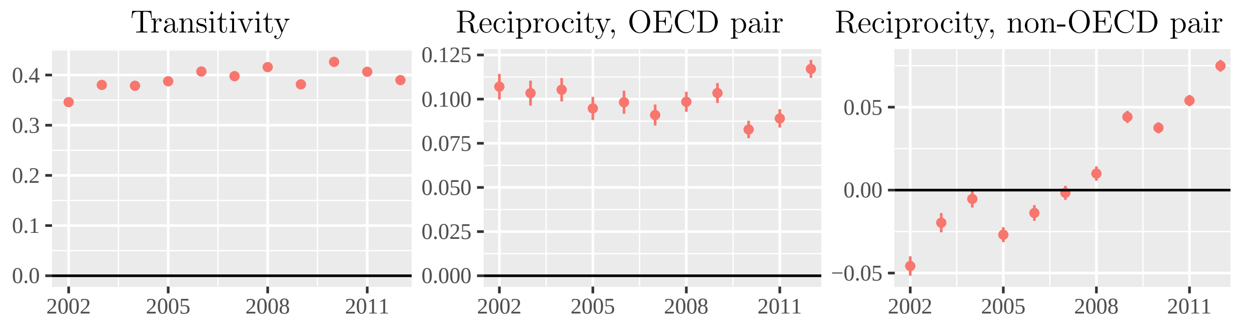


Figure G: Estimates of Dependence terms for models without tax havens. Bars span 95% confidence intervals.

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.

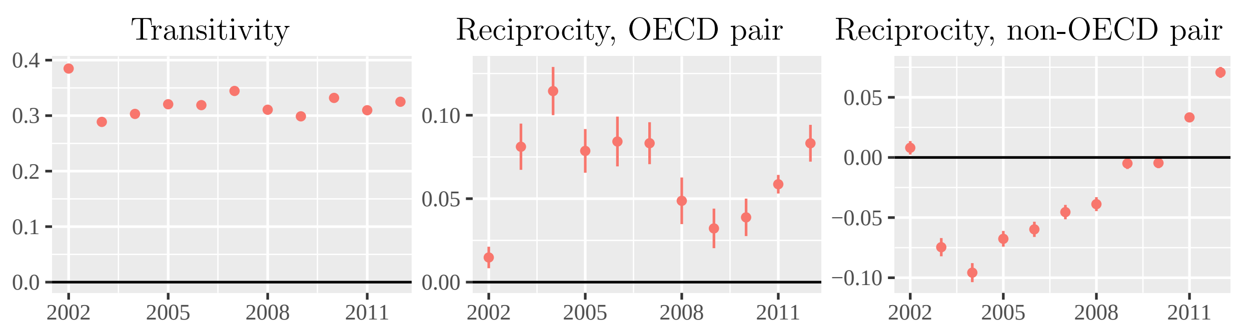


Figure H: Estimates of Dependence terms. Bars span 95% confidence intervals.

H Exchange rates and Inflation

FDI stocks can vary year to year due to reasons unrelated to FDI slows, 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 for 2007 for OECD pairs, but remain positive and significant for most years for OECD pairs and non-OECD pairs still pattern convergence by the end of the time sample.

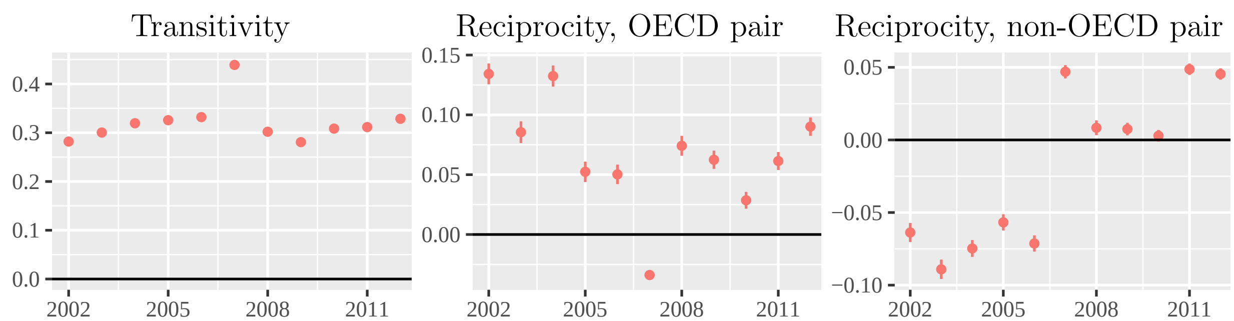


Figure I: Estimates of Dependence terms. Bars span 95% confidence intervals.

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