Applying Network Theory to International Processes: Application to Indirect Trade

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Abstract

The study of international relations (IR) has derived great benefits from recent advances in network analysis. Fast-paced progress in statistical modeling of networks within the study of IR, however, has not been matched by equal advances in theoretical understanding in outcomes related to such international networks as the trade, sanctions, or alliance networks. This is especially true for networks characterized by higher-order network relationships (e.g., triads, 2-stars, 4-cycles). This paper takes a first step towards a richer theoretical understanding of such complexities, by focusing on one of the more commonly used measures of dependencies—transitivity, or actors' tendency to form triangles. The paper explores the possible causal processes behind the formation of triangles in the international trade network and assesses the measurement validity of the commonly used transitivity measure as a proxy for the posited causal mechanisms. I do so by comparing the estimates associated with the transitivity measure of indirect trade flows between states to a corresponding instrumental variable measure.

Introduction

Social actors rarely act independent of one another's influences. Legislators confer before important votes (Kingdon 1973; Matthews and Stimson 1975) and seek one another's cosponsorships on legislation (Kirkland and Gross 2014); international firms channel goods through production chains in different states (Echandi, Krajcovicova, and Qiang 2015); international states are embedded within dense networks of trade, inter-governmental organizations (IGOs), and alliances (Maoz 2006, 2010; Chyzh 2016; Hays, Schilling, and Boehmke 2015).

Growing theoretical attention to the study of interdependence has, in turn, created a demand for more appropriate methodological tools that would allow to model such interdependence—a demand readily met by burgeoning statistical research in network analysis (Franzese, Hays, and Kachi 2012; Gile and Handcock 2015; Minhas, Hoff, and Ward 2016). While network analysis offers an ample variety of tools for modeling interdependence, the causal mechanisms behind many types of complex network dependencies remain largely unexplored (Ward, Stovel, and Sacks 2011). This paper takes a step towards a richer theoretical understanding of such complexities by zeroing in on the current theoretical and empirical applications of one of the common measures of network dependencies—transitivity or actors' tendency to form triangles. The central argument is that network analysis provides social scientists with more than just a statistical fix to the issue of non-independence among observations, but also a novel theoretical way of modeling and understanding interdependence. Maximizing the theoretical leverage of the network analysis tools, however, requires a careful examination of the causal processes for formation of particular network dependencies.

After providing a general overview of the current empirical and theoretical applications of the tools offered by network analysis, this paper explores the possible causal processes behind the formation of triangle structures in networks and assesses the measurement validity of the commonly used transitivity measure as a proxy for the posited causal mechanisms. In particular, I use Monte Carlo simulations to compare the measurement validity of the transitivity measure to an instrumental variable measure of the corresponding hypothesized (unobserved) processes in the network. Finally, I will supplement the Monte Carlo results with an empirical demonstration, comparing the transitivity measure of indirect trade flows between international states to a corresponding instrumental variable measure probabilistically constructed using a set of exogenous covariates.

Network Analysis and Theories of Interdependence

Recent research has recognized a natural fit between the growing demand for modeling theorized interdependence and a burgeoning methodological field of research on network analysis (Cranmer and Desmarais 2011; Maoz 2009). Network analysis treats actors as nodes that are embedded within a broader network (or graph) through their connections (edges) to other nodes (Carrington, Scott, and Wasserman 2005; Hoff, Raftery, and Handcock 2002; Snijders 2001; Wasserman and Faust 1994). Network dependencies are modeled via the inclusion of covariates that correspond to specific topological features of the graph (e.g., reciprocity, triads, 2-stars), which are defined as counts of all elements of a certain class that could potentially form in the given graph. The parameters associated with such covariates will then inform us of the prevalence of each type of element in the observed realization of the graph.

For example, a commonly specified triad model accounts for network dependencies via three covariates: the counts of all possible edges, all possible sets of edges that share a common node (a configuration known as 2-stars), and all possible sets of edges that can potentially form a triangle (Frank and Strauss 1986). The parameters on these covariates will then correspond to our estimates of the network density, clustering, and transitivity.

The density parameter is the ratio of realized edges and the total possible number of edges, given the number of nodes. A density parameter of 0.5, for example, indicates that in the observed network, each pair of nodes forms an edge with probability of 0.5, i.e. we expect that, given repeated draws of networks from a random distribution with a density parameter of 0.5, exactly 50% of all possible pairs of nodes will be connected by an edge. The clustering coefficient informs us of the probability of observing that two edges sharing a node will also share an edge, while the transitivity parameter is an estimate of the probability of two nodes sharing an edge, given that they are both connected to the same third node. Estimating these parameters can paint a broader picture of the type of the interdependencies within the data.

The central advantage of this approach, known as the ERGMs approach,[1] is that it allows researchers to isolate the effects of theoretically relevant covariates from the effects that may be observed merely due to actor non-independence. Given the well-established theoretical dependencies in social networks (networks of legislators, networks of firms, network of international states), a failure to account for these dependencies within the statistical analysis may result in biased estimates and incorrect inferences (Cranmer and Desmarais 2011). By applying an ERGM approach to the study of economic sanctions, for example, Cranmer, Heinrich, and Desmarais (2014) demonstrate that accounting for such network dependencies as density, reciprocity, isolates, 2-stars and 3-stars diminishes or effectively wipes out the effects of many covariates, previously theorized to affect a sender's decision to issue economic sanctions, such as a military alliance between the sender and the target, geographic distance between them, joint democracy, and the difference in Polity scores.

The main criticism of ERGMs, which often comes from more substantively oriented researchers, is that within the fields of international relations and political science, it is often

[1]Such models are often referred to as exponential random graph models (ERGMs) as their estimation usually involves the use of the exponential as the link function.

used as a "fix" of non-independence rather than a way to theoretically inform/enhance the model (Ward, Stovel, and Sacks 2011; Kirkland and Gross 2014). A central objective behind using ERGMs in most current applications boils down to factoring out the variance in the dependent variable that can be attributed to such non-independence. Once we control for all relevant/possible sources of non-independence (density, reciprocity, transitivity, clustering, etc.), the remaining variance must be attributable to the theorized dyadic or monadic covariates. Of course, the effectiveness of such "nuisance" approaches at factoring out "nuisance" variance, or variance due to non-independence, from the theoretically interesting variance hinges on the properties of the data we are working with. Given the known features of social science data (time-invariance, high levels of correlation among important covariates), applying such nuisance approaches may sometimes result in "throwing out the baby with the bathwater" or effectively crowding out the effects of the theoretical covariates, due to their time-invariance or high levels of multicollinearity (Beck and Katz 2001; Plümper and Troeger 2007, 2011).

Development of network-informed theories, in other words, seems to have lagged behind the use of network methods as effective statistical tools to alleviate the problems of non-independence among observations (Dorff and Ward 2013; Diehl and Wright 2016). While the research on network analysis tools as fixes of non-independence among observations is rich and growing (Gile and Handcock 2015; Krivitsky and Handcock 2014; Schweinberger and Handcock 2015), social science theories have been less successful at unveiling the causal mechanisms behind the effect of the increasingly complex network dependencies.[2] In fact, we continue to know very little beyond the most intuitive aspects about the causal mechanisms associated with the modeled effects of even the most common triad

[2]This is not to say that there has been no theoretical development. See, for example, Gallop (2016); Kirkland and Gross (2014); Larson (2016); Maoz (2010); Siegel (2009, 2011). The emphasis within international relations and social science more broadly, however, has tended towards using networks as methodological fixes rather than theoretical tools for deriving hypotheses.

model. In an article, intended as a methodological rather than a theoretical guide for the application of ERGMs to study international relations, Cranmer and Desmarais (2011) provide some very general theoretical mechanisms behind the effects of clustering and transitivity in models of international conflict initiation. A measure of clustering (via a count of 2-stars), in particular, may help account for the effect of "popularity": since international states are known to coordinate conflict initiation against a particular target, we should observe clustering in conflict initiation. Similarly, the argument regarding the effect of transitivity (actors' tendency to form closed triads) is based on the expectation that a war *between* two allies, currently at war with a common adversary, would be counterproductive.

An important and often over-looked nuance is that the utility of an ERGM model of conflict that includes 2-stars and triads depends on the study's focus on the role of interdependence in conflict outcomes. If actor-interdependence is merely a nuisance and presents no theoretical interest to the study, then including the network-level covariates of 2-stars and triads may in fact be the optimal approach to "fixing" the issue of non-independence of observations without distracting from the primary research question. It is important to recognize, however, that if interdependence among actors is the *primary* theoretical focus of the study, then network-level covariates are at most *second best* or an indirect way to measure the variables of theoretical interest. The most direct test of the aforementioned theory of multilateral cooperation on international conflict initiation is via a direct measure of multilateral coalitions membership, not via the count of possible 2-stars in the conflict network. The most direct test of the effect of common alliances is via a direct measure of alliances, not via the count of triangle structures.

This, of course, does not preclude network measures from serving as useful proxies for certain unobserved or difficult to measure effects. In a recent study of the US Congress, for example, Cho and Fowler (2010) take advantage of the clustering and transitivity coefficients, estimated for the network of legislative co-sponsorships, to construct a measure of the level of the transfer of ideas and creativity in Congress. Wilson, Davis, and Murdie (2016), likewise, take advantage of the network centrality measure to construct a proxy for the degree of pressure for peaceful conflict resolution (from international organizations) experienced by an international state in the midst of a crisis. Despite the recent growth in the use of network measures as proxies for hypothesized unobserved effects, scholars have devoted little attention to evaluating the measurement validity of such proxies—the goal of the current study.[3]

Admittedly, a comprehensive evaluation of the measurement validity of network measures as proxies for theoretical effects is beyond the scope of a single study, due to the large and expanding number of network measures. Instead, the current study will provide an in-depth analysis of one of the most commonly used network measures—transitivity. Transitivity, also referred to as "triads," "triangles," and "triplets" is the most common endogenous network-specific measure, included in network models (e.g., Berardo 2013; Berardo and Scholz 2010; Cho and Fowler 2010; Fischer and Sciarini 2016; Gerber, Henry, and Lubell 2013; Kinne 2013; Leifeld and Schneider 2012; Metternich et al. 2013).[4] In what follows, I define the measure in more formal terms, discuss the common theoretical mechanisms associated with its use, and conduct an assessment of its measurement validity using both Monte Carlo simulations and an empirical application to international trade.

The Theoretical Concept of Transitivity

The network measure of transitivity captures the nodes or actors' (positive or negative) tendency to form closed triangles. If we refer as a triad to any three actors within a network, then a triad is transitive if every pair of actors within a triad are connected by an edge (edges form a closed triangle). More formally, if $ij = 1$ denotes the presence of an edge between the nodes i and j (and correspondingly, $ij = 0$ denotes an absence of an edge), then triad ijk is

[3] For an important exception, see Kim, Antenangeli, and Kirkland (2017).

[4] Note that the common network measure of centrality is a node-specific, rather than network-specific, measure.

a transitive triad if $ij = 1$, $ik = 1$, and $jk = 1$. Examples of transitive triads may be found in a friendship network, where two individuals are more likely become friends if they have a friend in common. In contrast, a triad is intransitive, if the presence of two edges within it decreases the probability of a third edge, or if $ij = 1$ and $ik = 1$, then $jk = 0$. The logic that the enemy of my enemy is my friend may lead one to expect to find intransitive triads or negative transitivity in conflict networks (Cranmer and Desmarais 2011).

Triadic relationships of the type "the friend of my friend" or "the enemy of my enemy" have long attracted scholarly attention (Lee, Muncaster, and Zinnes 1994; Saperstein 2004; Maoz et al. 2007; Maoz and San-Akca 2015). A number of existing theoretical models of triadic relationships treat triadic relationships as transmission channels for goods or information (Dorussen and Ward 2008, 2010; Kinne 2012). Kinne (2013), for example, takes advantage of the triad measure to assess the hypothesized effect of treaties as channels of information regarding a potential future treaty partner (i.e., a treaty between A and B may allow A to gather information about party C, if there is a separate treaty between B and C). Building on these insights, Chyzh (2016) points out that triadic relationships may be endogenous to their effect, i.e. identifying the effect of such relationships may require first problematizing their formation/existence.[5]

As with other measures of network dependencies, a measure of network transitivity as a proxy for the flows of goods or information is particularly useful in empirical application that lack data on more direct measures of the theorized processes at work. Chyzh (2016), for example, uses a measure of transitivity in the international trade network as a measure of unobserved (and unobservable) illicit trade flows between states A and C through an intermediary B.[6] The author points out, in particular, that while a positive value of exports,

[5]Boehmke, Chyzh, and Thies (2016) suggest a methodological approach for accounting for endogeneity between network formation and effect.

[6]Consistent with (Helpman, Melitz, and Rubinstein 2008), this study models trade between pairs of states as a binary rather than a continuous edge, focusing on the first-order decision to trade rather than the second-order decision of "how much."

recorded by data collectors, is usually an accurate indication that the pair of states engages in trade, a record of 0 trade or no record (a missing value) are only indicative that the two states *did not report* any trade. Pairs of states that report no trade may do so for a number of reasons, including illicit trade or poor data collection. Since sanction-busters and smugglers are unlikely to report their illicit activities, a measure of intransitive triads, constructed from the existing data on observed directed trade flows (e.g., exports) between international states may serve as a convenient proxy for a measure of illicit trade.

To assess the measurement validity of such a measure, we must start with identifying the theoretical processes that may result in illegal trade flows between two states. According to Chyzh (2016), the primary theoretical mechanism is political conflict that results in a severing of observed trade ties between the two states. In particular, a measure of intransitive triads should serve as a particularly effective proxy of illicit trade if (1) two states cease economic and (possibly) political relations, due to a political disagreement (e.g, economic sanctions, military conflict), (2) yet at least one of the states in the pair continues to experience demand for the other's goods or consumer market. The latter condition would hold, for example, if one of the states had an absolute advantage in producing certain goods (e.g., there is a limited number of states that can sell oil) or if access to a substitute supplier were associated with significant costs (due to the lack of a relevant trade treaty, the absence of a trade route, etc.). The use of the intransitive triads proxy is particularly warranted for this particular type of illicit trade, as the first condition ensures the two states would have no observed trade, according to official reports. The second condition, in the meantime, is satisfied, as most shocks to the existing trade relationships (e.g., due to sanctions) impose the costs of finding alternative suppliers or markets on both the target and the sender (Kaempfer and Lowenberg 1988; Bapat and Kwon 2015). Moreover, since the modern international trade network is rather dense (most states exchange at least some trade with most other states), an absence of an observed trade relationship is, in many cases, more indicative of either the scholarly ability to collect data or the quality of the official reports rather than the actual absence of trade exchange.

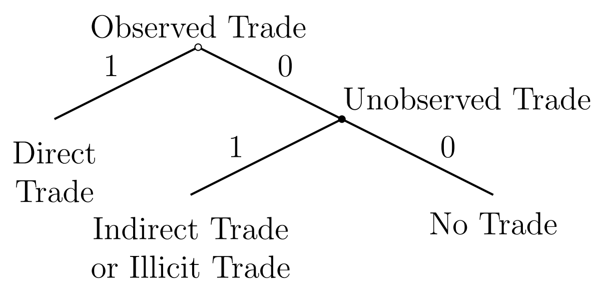
Assessing the validity of a particular network measure also warrants asking whether that measure is likely to pick up other possible relationships in the network than the ones posited by the theory. Depending on the quality of the official trade records, a measure of intransitive triads may, for example, also pick up legal trade flows, such as those that result from firms taking advantage of economies of scale. If the official trade reports fail to accurately trace the movement of goods through legal supply chains, such as the transit of goods through major trade hubs like Amsterdam or Los Angeles on their way to their intended destinations, then the intransitive triads measure may also pick up amounts of trade associated with these legal flows.

Finally, the intransitive triads measure may pick up trade flows through intermediaries that are due to a lack of infrastructure in the destination market. For example, in the immediate aftermath of US removal of economic sanctions against Myanmar, the Coca-Cola Company channeled its trade to Myanmar through the neighboring states, before the required infrastructure in Myanmar was rebuilt (New Zealand Herald 2012).

Intransitive Triads as a Measure of Unobserved Trade

In this section, I will assess the measurement validity of the *Intransitive triads* as a proxy for the indirect trade flows between international states first using Monte Carlo simulations and then estimating a theoretically informed empirical model of indirect trade. The theoretical process, described in the previous section, is presented in Figure 1. Available trade datasets (e.g., World Bank 2016; Barbieri and Keshk 2012) report known trade amounts for each pair of international states, for which such data are available. Importantly, no reported trade exchange does not mean that in actuality the two states engage in no trade. Missing

Figure 1: The Theoretical Model of Trade



or zero trade values in trade data may indicate one of two outcomes: (1) the two states in fact did not directly exchange any goods in a given year or (2) the two states engaged in trade—either indirect trade or illicit smuggling—but no reliable data were collected, i.e. the pair of states did not report their trade volume or their reports are known to be unreliable (Boehmer, Jungblut, and Stoll 2011). According to the theoretical argument outlined above, many dyads that report no trade (or do not report any data at all) are likely to trade indirectly: lack of data may indicate illegal trade or trade channeled through intermediary states (i.e., there may not be accurate records). Each observation in the trade data for which no data is recorded (missing or 0 values) is therefore a suspect for indirect trade.

In order to assess the measurement validity of *Intransitive triads*, I therefore start with simulating data using a data-generating process (DGP) that mimics the causal model displayed in Figure 1 and described above. In particular, the data is simulated using a two equation split-population DGP. Let τ be a random realization of a latent variable, τ^*, such that τ takes on the value of 1 if a pair of nodes share an edge (we may think of an edge as denoting either direct or indirect trade exchange), and 0 otherwise. More formally:

$$\tau^* = Z\gamma + \nu \tag{1}$$

so that $\tau = \begin{cases} 1 \text{ if } \tau^* > 0 \\ 0 \text{ if } \tau^* \leq 0, \end{cases}$

where Z is an exogenous covariate, γ is a model parameter, and ν is random error.

Next, let R be a random realization of a latent variable R^*, which models the probability of data being observable and recorded. More formally:

$$R^* = X\beta + \epsilon \tag{2}$$

so that $R = \begin{cases} 1 \text{ if } R^* > 0 \\ 0 \text{ if } R^* \leq 0 \end{cases}$

where X is an exogenous covariate, β is a model parameter, and ϵ is the random component. The probability of each outcome of the dichotomous random variable Y depends on the realizations of both τ (probability of an edge between two nodes) and R (the probability of this edge being observed and recorded). More formally:

$$\mathrm{P}\left(Y_i = 1\right) = \mathrm{P}(\tau) * (\mathrm{P}(R)), \tag{3}$$

$$\mathrm{P}\left(Y_i = 0\right) = (1 - P(R)) * \mathrm{P}(\tau) + (1 - \mathrm{P}(\tau)). \tag{4}$$

In accordance to the posited theoretical process, the dependent variable Y takes on the value of 1 if a pair of nodes shares an edge ($\tau = 1$) and this edge is observable ($R = 1$). Otherwise, if a pair of nodes does not share an edge ($\tau = 0$, $R = 0$), or a pair of nodes shares an edge ($\tau = 1$), but this edge is unobservable ($R = 0$), Y takes on the value of 0.

Knowing the DGP, of course, we can write out the likelihood function as:

$$L = \prod_{i=1}^{N} \mathrm{P}\left(Y_i = 1\right)^{y_i} \mathrm{P}\left(Y_i = 0\right)^{1-y_i} \tag{5}$$

where Y_i is the value of the random variable for the individual observation i and N is the number of observations.

The above likelihood represents a mixture model with a binary outcome (Xiang 2010). Equation 3 estimates the probability of an edge that is observed, e.g., a pair of states exchanges goods and this exchange is recorded by data-collectors. Equation 4 models both types of 0 outcomes in the data: (1) the probability of an edge that is not observed, e.g. two states exchange trade, but this exchange is not recorded; and (2) the probability of no edge. Assuming that the errors are independent and identically distributed following a logistic distribution with mean 0 and variance $\frac{\pi^2}{3}$, we can estimate the two random variables as:

$$P(\tau) = \frac{e^{Z\gamma}}{1 + e^{Z\gamma}}, \tag{6}$$

$$P(R) = \frac{e^{X\beta}}{1 + e^{X\beta}}, \tag{7}$$

The measurement validity of *Intransitive triads* for this application can be then assessed by comparing *Intransitive triads* to the true values and the estimates of the model.

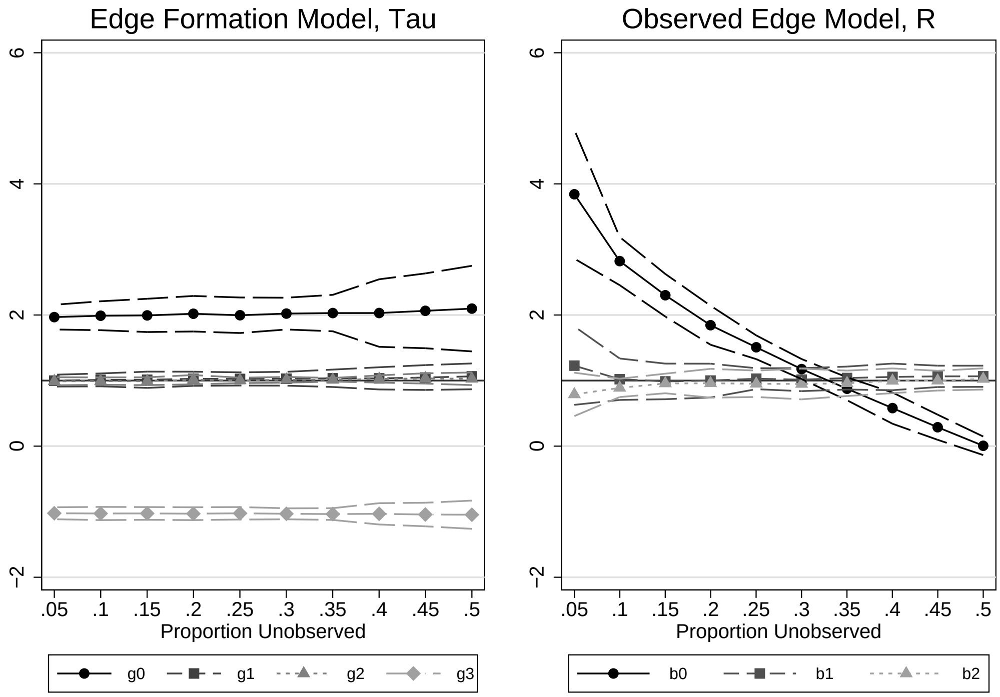
Monte-Carlo Simulations

As the goal of the study is to evaluate the measurement validity of a theoretical network measure, the data used in the simulations must be characterized by spatial non-independence—a central feature of network data. To achieve this, the simulations data is generated by following the steps described below. I start with generating information for 100 nodes (units) $i = 1, 2, \ldots, n$ with characteristics captured by variables Z_i and X_i, both of which have a standard normal distribution. I then create a dyadic version of these data by pairing each node with each other possible node (units of the type $i - i$ are omitted) for a total of 9900 observations, with the directed dyad as the unit of observation. To introduce network dependencies, I then place each node on an evenly spaced ten-by-ten grid and calculate the Euclidean distance between the two units in each dyad to generate a dyadic variable, D_{ij}. The dependent variables, τ_{ij} and R_{ij}, are then functions of both node-specific variables, Z_i and X_i. In addition, to remain consistent with a network's set-up, the probability of a true ties, is also a function of distance, D_{ij}.

The results, based on 500 Monte Carlo simulations, are presented in Figure 2. To explore the effect of unobservability of edges, I vary the threshold of R_i^* to produce data with different proportions of unobservable edges (between 5% and 50%). The true coefficient values are set as $\gamma_0 = \gamma_1 = \gamma_2 = 1$, $\gamma_3 = -1$ (the corresponding covariate is a measure of dyadic distance, D_{ij}), $\beta_0 = \beta_1 = \beta_2 = 1$. As expected, the split-population model is able to correctly recover all the coefficients for all variables. The model, however, does not perform as well on recovering the intercept in either equation: the intercept in the *Edge formation* equation, τ_{ij}, is over-estimated by a constant amount for all levels of unobservability, while the bias in the intercept in the *Observed edges* equation, R_{ij}, is inversely related to the number of unobserved edges. The size and direction of bias in the intercept in the *Observed edges* equation, of course, is consistent with the estimation structure, imposed by the model: when the proportion of unobserved links is very low (5%), the model "over-corrects" by estimating an inflated value of the intercept. This bias goes away as the number of unobserved ties increases in the data.

Of course, our substantive goal is not to simply estimate unbiased parameters on our theoretically relevant variables, but to correctly classify observations given the appropriate underlying theoretical process. In other words, we must evaluate the model's ability to separate the two types of unobserved edges into (1) unobserved due to no edges (e.g., no trade flows) and (2) unobserved due to data-collection impediments (e.g., illegal trade, difficult to track intermediated trade)? Figure 3 summarizes the model's ability to correctly predict the second type of edges as well as the corresponding measure of incorrectly predicting an non-

Figure 2: Estimates of Coefficients

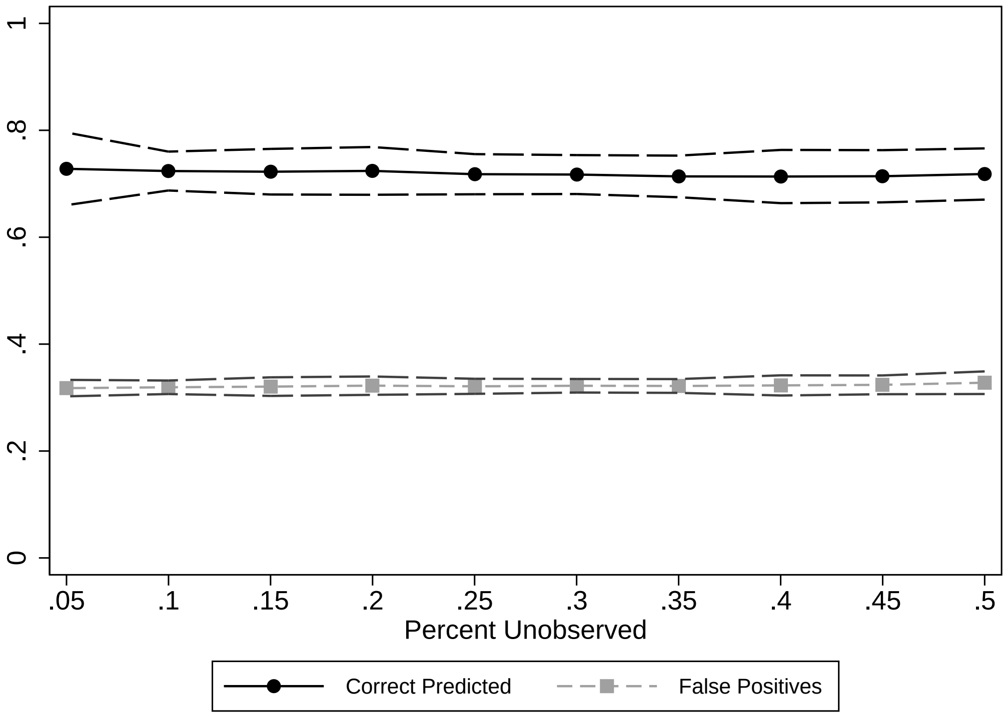


Note: Estimates are based on 500 simulations for each threshold of unobserved edges. The true values are $g_0 = 1$, $g_1 = 1$, $g_2 = 1$, $g_3 = -1$, $b_0 = 1$, $b_1 = 1$, $b_2 = 1$.

existing edge (false positives). Notably, the model is able to correctly predict existing yet unobserved edges approximately 70% of the time. Moreover, the model's predictive ability is not affected by the proportion of unobservability in the data.

To compare the proposed approach to the alternative of modeling the network's tendencies via the inclusion of network-specific covariates, I re-estimate the simulated networks using an ERGM with a *Triangle* covatiate. The estimated coefficients on *Triangles* for each level of unobserved ties are presented in Figure 4. We can see that the coefficient on *Triangles* is highly sensitive to changes in the observed network configuration (i.e. changes in the level of unobserved ties). The ERGM estimates suffer from two problems: first, while ERGMs purport to capture higher-order network dependencies via inclusion of the theorized

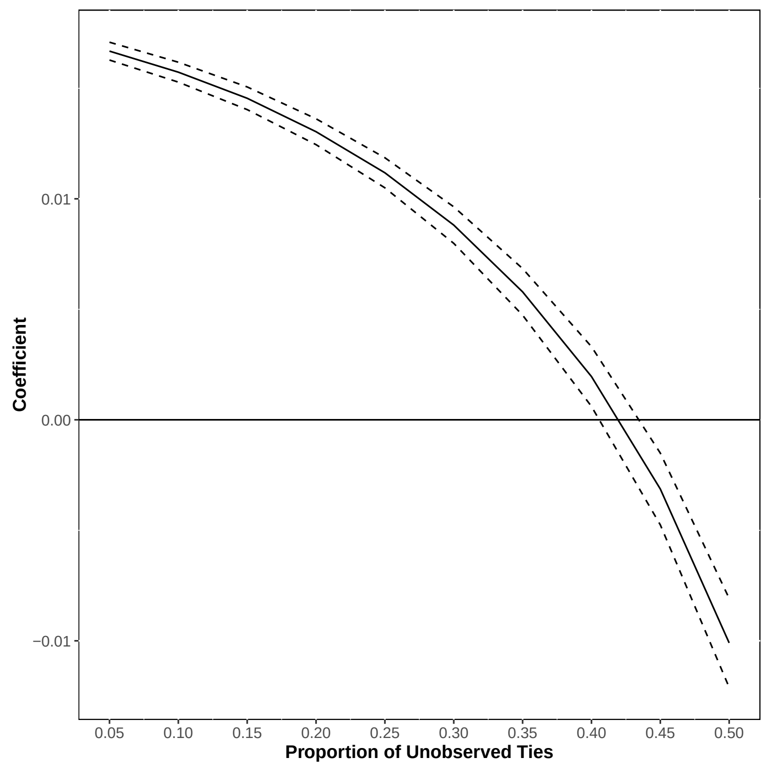
Figure 3: Predicted Probabilities of Unobserved Edges



Note: The probability of correctly predicting unobserved edges is the average of $\widehat{P}(\widehat{\tau}_i = 1|\tau_{ij} = 1, R_{ij} = 0)$. The probability of a false positive is the average of $\widehat{P}(\widehat{\tau}_i = 1|\tau_{ij} = 0, R_{ij} = 0)$.

network topologies, such as triangles here, the recovered coefficient is difficult to interpret in terms of magnitude. The estimated coefficient, moreover, provides few theoretical insights about the network beyond the obvious observation that networks with lower levels of unobservability have more triadic configurations, The coefficient on *Triangles*, moreover, offers no information regarding *where* in the network the triadic configurations appear or whether the absence of a triad indicates a lack of trade or a lack of recording trade. Second, and more troubling, is that the direction of the estimated effect changes as the proportion of unobserved ties increases; that is, under some conditions, inferences based on these estimates will be *opposite* to the true relationship. Taken together, if the type of data at hand suffer

Figure 4: ERGM Estimates of *Triangles*



Note: Estimates are based on 100 simulations for each threshold of unobserved edges. Dashed lines correspond to a 95% CI.

from possible unobservability or are otherwise incomplete (e.g., a subsample), then a naïve ERGM estimation may obfuscate rather than elucidate the true effects of the variables.

Finally, the probabilistic estimation of unobserved edges compares favorably with the *Intransitive Triads* proxy for the same theoretical process. Since the *Intransitive Triads* is not theoretically informed, it will count any "open triangle" in the data as an indirect edge, without any ability to separate a type 1 indirect edge (an indirect link between two nodes that is a mere artifact of the network) from a type 2 edge (a theoretically relevant indirect edge that may be used as a channel of goods or information). While this theoretically uninformed measure will have 100% of correct positives (i.e. it will correctly identify all type 2 edges as theoretically relevant), it will also have 100% false positives (i.e. it will falsely identify all type 1 edges as theoretically relevant). The theoretically relevant measure of "unobserved ties," in other words, is not accurately measured by the "off-the-shelf" proxy, such as *Intransitive triads*.

Application: International Trade

To further evaluate the measurement validity of *Intransitive triads* and the proposed instrumental variable approach, I next apply the above method to the empirical example of international trade. For this purpose, I estimate a split-population model of international trade by regressing *International trade* on a set of commonly used theoretical predictors associated with the pairwise probability of engaging in trade relationships and a set of predictors associated with reporting trade data. The first equation, *Probability of trade*, includes such variables as GDP, GDP/capita, distance between the two states, while the second equation, *Probability of Observing Trade* includes measures of rule of law, democracy, resource rents,[7] participation in a civil or international war, and the presence of bilateral sanctions.

The dependent variable, *International trade*, is measured as a binary variable that equals 1 for pairs of states ij if i exported any goods to j in a given year, according to Barbieri, Keshk, and Pollins (2009), and 0 otherwise. The unit of observation is a directed dyad-year. All other economic variables (GDP, GDP/capita, resources) are obtained form the World Bank (2016), distance is obtained from Weidmann, Kuse, and Gleditsch (2010), rule of law is measured via the judicial independence variable constructed by Linzer and Staton (2012), democracy is measured using the *Polity 2* variable of Marshall and Jaggers (2014), civil and international war data are obtained from Sarkees and Wayman (2010), and bilateral sanctions are measured as a binary dummy if either of the states within a dyad are reported to issue economic sanctions against the other in a given year, according to Morgan, Bapat, and Kobayashi (2014). All economic variables are log-transformed to ac-

[7] Resource rents is measured as the total of mineral, oil, and natural gas receipts (World Bank 2016).

count for skewness.

Estimating a split-population model requires specifying two separate simultaneously estimated equations: (1) *Edge formation* or *Expected trade* and (2) *Edge observability* or *Observed trade*. The *Edge formation* equation is specified using the traditional components of a gravity model, such as GDP, GDP/capita, and distance, as well as resource rents. For the purposes of statistical identification between the two equations, the first equation also includes a country-specific percentage of endemic species (mammals) of the total number of known species (*Biodiversity Data Sourcebook* 1994). The *Endemic species* variable is a useful identification tool, as biodiversity is largely exogenous to international trade, yet presents a rather accurate proxy for geographical remoteness/isolation—a known correlate of trade (e.g., states are more likely to send trade to easily accessed locations). The *Edge observability* equation is specified using variables that may affect data-collectors' ability to access accurate data: rule of law, democracy, involvement in civil or international wars, and economic sanctions.

The estimation results are presented in Table 1. All variables act consistent with previous findings in the literature. Rather than the coefficients, however, the focus here is on the model's ability to probabilistically separate pairs of states that do not trade from the pairs of states that do trade, but whose trade is not reported. A list of the pairs of states that are identified by the model as the most likely suspects for engaging in unreported trade is presented in Table 2. Finally, to assess the measurement validity of the instrumental variable approach, relative to *Intransitive triads* proxy, Table 3 lists a sample of state-pairs that, though identified by the *Intransitive triads* proxy, have a very low predicted probability of actually exchanging trade flows.

It is also worth noting that, unlike the instrumental variable approach, the *Intransitive triads* measure is extremely sensitive to missingness in the data: for example, states with no reported data (no exports to any states) due to sanctions, conflict, or non-reporting, will

Table 1: International Trade: Expected and Observed

Expected Trade Eqn, τ_i:		
GDP A	0.857*	(0.005)
GDP B	0.656*	(0.005)
GDP/cap A	0.112*	(0.005)
GDP/cap B	0.198*	(0.005)
Distance	-1.062*	(0.009)
Resources A	-0.187*	(0.003)
Resources B	-0.099*	(0.003)
Endemic Species A	0.007*	(0.000)
Endemic Species B	0.002*	(0.000)
Constant	-28.287*	(0.160)
Observed Trade Eqn, R_i:		
Rule of Law A	0.473*	(0.155)
Rule of Law B	1.256*	(0.137)
Polity A	0.091*	(0.006)
Polity B	0.042*	(0.005)
Civil War A	-0.856*	(0.038)
Civil War B	-0.679*	(0.038)
War	-1.030*	(0.089)
Sanctions	-0.963*	(0.088)
Constant	2.669*	(0.103)
N (dyad-years)	383,042	
Years	1970-2008	

Note: $^*p < 0.01$. The dependent variable is *International Trade*, coded as 1 if A reported any exports to B in a given year. *International Trade* has a mean of 0.35 and sd of 0.47.

be identified as "isolates" by network measures. The instrumental variable approach, not sensitive to the structural network assumptions, by contrast, is still able to assign positive probabilities of (unreported) trade for such states. Iran, Iraq, Egypt, Israel, Armenia and Azerbaijan figure prominently as likely suspects in Table 2, yet are "missed" by the *Intransitive triads* proxy, due to poor data reporting and sanctions. Despite the challenges associated with a systematic verification of illegal trade flows, one is not hard-pressed to find anecdotal evidence of uncovered smuggling attempts between Iran, Armenia and Azerbaijan, especially through the "frozen" war-zone in Nagorno-Karabakh (Armenian News 2012; Armenpress 2013; News.Az 2015).

To further explore the validity of the instrument, it may be useful to look at some

Table 2: Predicted Unobserved Export Flows (1970-2001)

Exporter	Importer	Years	Probability (period average)	COW Trade Data Record
Iran	Iraq	1974	0.69	0
Iraq	Iran	1982-1988	0.67	0
Iran	Iraq	1980-1988	0.66	0
Iraq	Iran	1980-1981	0.62	0
Iraq	Saudi Arabia	1973	0.55	0
Iraq	Iran	1973	0.55	0
Algeria	Morocco	1979,1984	0.53	0
Congo DR	Uganda	1987, 1996,1998-1999	0.52	0
Iran	Iraq	1989	0.49	0
Morocco	Algeria	1979,1984	0.48	0
Israel	Egypt	1970,1973	0.47	0
China	Iran	1974	0.45	Missing
Zimbabwe	Zambia	1977-1978	0.45	0
Uganda	Congo DR	1987,1996,1998-1999	0.43	0
Zambia	Zimbabwe	1976-1977,1979	0.43	0
South Korea	Iraq	1982	0.41	0
Armenia	Azerbaijan	1993-1994	0.41	0

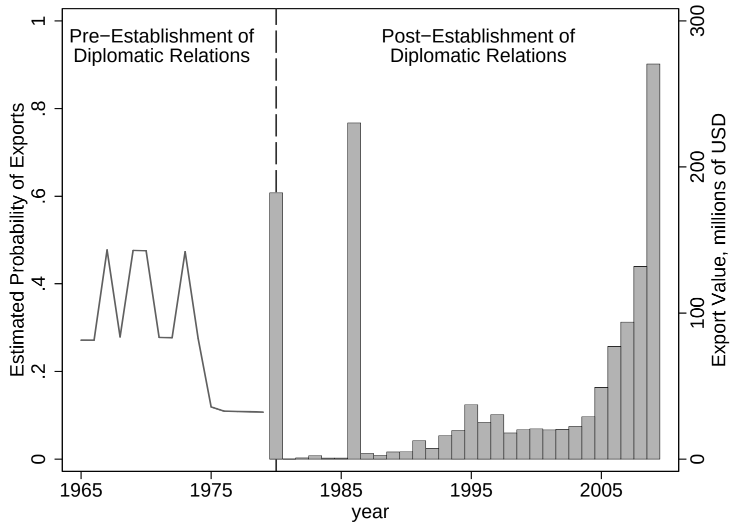
Note: These data include pairs of states with the highest predicted probabilities of unreported exports.

Table 3: Estimated Probabilities of Trade Flows between Non-Theoretically Derived *Intransitive Triads*

Exporter	Importer	Years	Probability (period average)	COW Trade Data Record
Solomon Islands	Liberia	1990-2008	0.00003	Missing
Gambia	Solomon Islands	1990-2008	0.00003	Missing
Liberia	Solomon Islands	1990-2008	0.00004	0
Solomon Islands	Gambia	1990-2008	0.00004	Missing
Solomon Islands	Suriname	1990-2008	0.00006	Missing
Moldova	Solomon Islands	1992-2008	0.00007	Missing
Solomon Islands	Central African Republic	1990-2008	0.00007	Missing
Central African Republic	Solomon Islands	1990-2008	0.00007	0
Suriname	Solomon Islands	1990-2008	0.00007	Missing
Malawi	Solomon Islands	1990-2008	0.00007	0
Solomon Islands	Moldova	1992-2008	0.00008	Missing

Note: The list include pairs of states that are identified as *Intransitive triads* and are in the bottom 10 in terms of predicted probability of trading, based on the estimates from Table 1.

Figure 5: Egypt—Israel Exports, 1965–2010



Note: Solid line represents the estimated probability of exports before the establishment of the diplomatic relations in 1980. Bar graph shows Egypt's reported value of exports to Israel, according to Barbieri, Keshk, and Pollins (2009).

additional evidence from a specific illustrative case. The current analysis, in particular, consistently estimates a high probability of unreported exports flows from Egypt to Israel. Consistent with these reports, Figure 5 displays the estimated predicted probability of exports from Egypt to Israel, calculated using the estimates from Table 1 and the reported values of Egypt's exports to Israel. Specifically, Figure 5 highlights several patterns that give further credence to the validity of the instrumental variable measurement approach.

First, despite the lack of the diplomatic relations between the two countries prior to 1980, and the corresponding reports of no exports, the estimated probability of unreported exports is consistently always above 10% and reaches as high as 48% in the 1967, 1969, 1970 and 1973. Second, the officially reported trade numbers in the immediate aftermath of the establishment of diplomatic relations exhibit significant fluctuation: a drop from $182.3 million in 1980 to $0.1 million in 1981, then remaining consistently low until another jump to $230.15 million in 1986 and a drop back to $3.8 million in 1987. Since the actual trade volumes are unlikely to go through such drastic year-to-year fluctuations (i.e. a more consistent increasing post-1987 pattern in volumes seems more credible), the size of these fluctuations may be instead indicative of changes in data collection and reporting practices (e.g., reporting previously unreported trade volumes).[8] While the lack of data precludes a definitive conclusion regarding the presence, nature, or make-up of the trade-flows between the two states, the model identifies the pair as a likely suspect for exchange of contraband, obtaining re-packaged goods originating from blacklisted companies, or serving as markets for lower quality legal substitutes of such goods (Barbieri and Lewis 2015).

To place some context around the estimates, one must remember that Egypt was one of the original parties to the Arab League Boycott that prohibited primary, secondary, and tertiary trade with Israel.[9] Egypt-Israel relations, however, were normalized as a result of a 1979 Peace Treaty, largely due to the US pressure, as well as an economically draining arms race between the two states, and—most importantly for the current analysis—Israel's inability to meet its growing demand for oil through domestic production. Egypt's consent to allow Israeli bids on Egyptian oil was, in particular, a key part of the Peace Treaty (Engber 2006). It is also notable that Israel's sources of oil imports are largely unconfirmed, due to secrecy aimed at protecting the cooperating companies from being blacklisted by the Boycott.

Given the context, the high predicted probabilities of Egypt–Israel exports, displayed in Figure 5, are not necessarily indicative, although also do not preclude, the existence of illegal

[8] Likewise, Reuveny and Kang (1996, 592) describe some of these inconsistencies in the data as being due to differences in UN and IMF reports.

[9] Primary boycott prohibited direct trade between companies within the participating countries and Israel, secondary boycott prohibited domestic companies from conducting business with Israel-friendly foreign companies, while the tertiary boycott prohibited relationship with foreign companies that deal with Israel-friendly companies indirectly (Campbell 1980). Despite the boycott's severity and comprehensiveness, there are reports of numerous loopholes, exceptions, and violations that raise doubts about the quality of the officially reported trade data among the affected countries (Campbell 1980; Barbieri and Lewis 2015). Campbell (1980, 38), for example, compares Saudi-issued version of the "boycott blacklist" of US companies to those on the Fortune 500 list for the corresponding year to find that "only about five percent of the 100 companies checked were on the boycott blacklist."

pre-1980 oil exports from Egypt to Israel. Whether oil originating from Egypt ever reached Israel or not, there is some evidence that Israel's demand for foreign oil was indeed partially fulfilled by secret imports originating in one or several of the boycotting states,[10] while these illegal sales opened up other oil markets for companies that chose to follow the boycott.

Conclusion

The paper highlights a need for more careful theorizing regarding the processes that lead to formation of social and political networks of interest, as well as the possible effects of these networks on actors that make them up. While existing network measures, such as triads or 2-stars, may function as proxies for theorized network dependencies, such proxies may have substantial limitations in terms of measurement validity (see also Kim, Antenangeli, and Kirkland 2017). A theoretically-guided probabilistic instrumental variable approach to measuring indirect and unreported trade is shown to outperform a *Intransitive triads* proxy.

The broader argument extends beyond the current empirical application and helps delineate the advantages and limitations of relying on off-the-shelf network measures and inferential network analysis. Network analysis offers diverse theoretical and methodological techniques, but the suitability of any given approach is application specific. If possible network dependencies among observations are merely a nuisance, then off-the-shelf measures of network dependencies, such as triads, 2-stars, and reciprocity, may function as an effective tool for factoring out the unwanted correlations in the data. The off-the-shelf network measures, however, are only rough proxies for theorized network dependencies and are frequently not tailored for particular empirical applications, and may be easily improved upon (in terms of measurement validity) by alternative measurement approaches. If interdependence among observations is the primary theoretical focus of analysis, the goal of such research may be

[10]For example, the 1979 Iran oil crises indicated that a large portion of Israel's oil might have originated in Iran (Phillips 1979).

better served by forgoing the off-the-shelf network measures in favor of measures that are directly derived from the theoretical model. As demonstrated by the empirical application, theoretically derived measures may provide substantial improvements in measurement validity, even under the conditions of unobservable processes (e.g., information flows) or in the absence of available data or data that may sometimes experience inaccurate recording (e.g., illegal and indirect trade; tourism, migration, and refugee flows).

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