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Measuring International Relations using Latent Network Approach

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Measuring International Relations using Latent Network Approach

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Natalia Lamberova

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ABSTRACT OF THE THESIS

Measuring International Relations using Latent Network Approach

by

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Master of Science in Statistics
University of California, Los Angeles, 2020
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International political relations are hard to characterize, as they depend on the network of state relationships. Important political alliances between two countries are often made with the help of other countries, international conflicts often require mediation, efforts of countries to tackle complex issues often require coordination of many states. Hence, it is important to gauge the network structure of international relations when accessing relation between any pair of countries.

Many current approaches rely on existing alliances or conflicts to characterize government-to-government interactions at a given point in time, but these are often the outcomes of ongoing negotiations or mounting conflicts, and thus are more likely to characterize past relations, rather than relations of the current period. In recent years, the availability of data capturing day-to-day interactions of countries has increased dramatically, greatly increasing the number of dimensions to be captured, and providing scholars with an opportunity to explore the network of smaller-scale country-to-country interactions.

This thesis proposes a way to characterise state-to-state relations in a context of the whole network of international relations in a given year applying latent network approach proposed by Hoff, Raftery and Handcock (2002) to summarized

Integrated Crisis Early Warning System (ICEWS) events dataset. Under the latent space framework the probability (magnitude) of a relation between countries depends on the positions of countries in an unobserved "social space." These positions are estimated within a Bayesian framework, using Markov chain Monte Carlo procedures to infer latent positions. I validate the resulting measure of government-to-government relations by demonstrating that they are strong predictors of international trade, outperforming the most commonly used measured of state relations, known as the S-Score (Signorino and Ritter, 1999).

The thesis of Natalia Lamberova is approved.

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Chad J. Hazlett

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Mark Stephen Handcock, Committee Chair

University of California, Los Angeles

2020

To my friends, who always inspire me

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CHAPTER 1

Introduction

International political relations are hard to characterize, as they depend on the whole network of state-to-state relationships. The dyadic country-to-country relations are not formed in a vacuum. Important political alliances between two countries are often made with the help of other countries, international conflicts often require mediation, efforts of countries to tackle complex issues often require coordination of many states. Hence, it is important to gauge the network structure of international relations when assessing relation between any pair of countries. Yet, when unmeasured, political relations between a pair of countries constitute an omitted variable in many contexts. A number of studies have shown that political relations impact a plethora of outcomes, ranging from expected course of military coalitions and wars (Wolford, 2015; Kinne, 2018) to economic cooperation (Mansfield and Bronson, 1997; Long, 2003).

Many current approaches rely on existing alliances or conflicts to characterize government-to-government interactions at a given point in time (e.g. Maoz and Russett, 1993; Owen, 1994), but these are often the outcomes of ongoing negotiations or mounting conflicts, and thus are more likely to characterize past relations, rather than relations of the current period. The most common approach to modeling state interests in international affairs today is a measure of foreign policy similarity – the S-score (Signorino and Ritter, 1999). Many influential studies have successfully employed this measure in the analysis (see Bennett and Rupert, 2003, for a review).

While highly useful, the S-score measures the similarity of states' interactions with foreign states rather than the relationship between those states. Ideally, one wishes to construct a measure that captures the probability (value) of a tie formation between two countries given the existence (values) of other ties in the network. In order to construct such a measure, I follow Hoff, Raftery and Handcock (2002) and utilize a notion of "social space" - a space of unobserved characteristics of the countries, such that countries with a large number (value) of ties between them indicate nearby positions in this space of these characteristics. Under their formulation, the relations are probabilistically transitive in nature: if country A is connected to country B, and country B is connected to country C, than countries A and C are likely not far apart in social space, and are more likely to have a tie. I characterise country-to country relations by taking the euclidean distance between countries in this latent space. In this project, the latent space is constructed based on an events dataset called the Integrated Crisis Early Warning System (ICEWS).

I characterise measures of country-to-acountry connections in two ways, utilizing two subsets of international interactions containing positive and negative interactions, respectively. One assumes the existence of separate "affinity" and "antipathy" "social spaces" and measures the distance between countries in them. Another focuses on the wieghted sum of direct country-to-country interactions withough taking the ties with other countries into account.

This thesis proceeds as follows. Chapter 2 discusses the existing approaches to summarizing country-to-country interactions. Chapter 3 provides the overview of the data that is used to build the network, as well as the approach to summarizing it. Chapter 4 briefly discusses the application of the latent network approach to the data and the resulting measures. Chapter 5 examines the performance of the proposed measures on a small set of cases. Chapter 6 validates the proposed measures by applying them to predict country-to-country trade flows. Chapter 7 concludes.

CHAPTER 2

Existing Approaches to Measuring Country-to-Country Relations

Many theories in the field of international relations invoke a measure of state-to-state realations and require constructing such a measure for empirical tests. For many years, a simple rank correlation measure over a group of policy measures (Kendall's τ_b) was commonly used as a proxy for state reliations. It measures the extent to which states i and j rank their alliance commitments to other states in the same order, meaning that it had several important shortcomings. First, perfect negative association could occur even if states had somewhat similar alliance policies. Second, τ_b could differ even in cases where the alliance portfolios were similar. For these reasons, it has been replaced by S-scores in more recent years (see Signorino and Ritter, 1999 for a review). The S-score captures whether two countries have alliances with, fight with, and trade with similar sets of states, for example. It is often taken to be a measure of relationship quality and of the similarity of state interests.

However, S-scores do not take into account two important characteristics of foreign policy ties: formalized alliance formations are relatively rare (compared to all possible alliances in the network) and individual states differ in their innate probability to form an alliance. While useful for capturing baseline policy similarity, the most commonly used S-score, Bennett and Stam (2000), varies little over time, even in cases known to contain significant shifts in state relationships. For example, when analyzing pitfalls of using S-scores, Hage (2011) shows (using 1950-1990 data) that traditional S-scores fail to recognize important shifts resulting from the collapse of Soviet Union. He introduced a corrected measure, mitigating these issues.

Another approach is focused on quantifying relations between countries, not their policy similarities. Formal alliances between countries is the most common source of data for these purposes. For instance, Benson and Clinton (2012) look at the strength of alliances signed between 1816 and 2000, bawed on the strength of the signatories and strength of the formal terms of alliance, using Bayesian latent variable model. The meaning of an alliance can also depend on participant's reputation for hostility. Crescenzi (2007) introduced a framework, where states consider their opponents' historical ties with other nations, but they weigh the degree to which these other nations are similar to themselves. Yet, as many other measures, it relies on high-impact events, such as existing military alliances, to calculate the similarity of policy portfolios for each dyad of states. While these approaches allow one to account for the formally existing alliances, they do not rely on the information about interactions between countries not encoded in formal agreements. More recent measures try to incorporate additional indicators of military cooperation, while also accounting for the degree of third-party alliances, and standardizing the measures of policy similarity (Orazio, 2013).

An alternative approach, taken up here, is to rely on the massive amount of "events" data already publicly available, which reports on newsworthy events that are far less substantial (and more common) than formal agreements. In recent years, the availability of data capturing day-to-day interactions of countries has risen dramatically, greatly increasing the number of dimensions to be captured, and providing scholars with an opportunity to explore the network of smaller-scale country-to-country interactions.

This thesis proposes a way to characterise state-to-state relations in a context of the whole network of international relations in a given year applying latent network approach proposed by Hoff, Raftery and Handcock (2002) to the ICEWS events dataset, discussed in Section 3. Under this latent space framework, the probability (magnitude) of a relation between countries depends on the positions of countries in an unobserved "social space." These positions are estimated within a Bayesian framework, using Markov chain Monte Carlo procedures for making inference on the latent positions. I validate the resulting measure of government-to-government relations by demonstrating that they are strong predictors of international trade, outperforming the most commonly used measured of state relations – the S-score .

CHAPTER 3

The integrated early warning system dataset and summaries

The Integrated Conflict Early Warning System (ICEWS) is a machine-coded events dataset covering a time period from 1996 to 2016. It was first described in O'Brien (2010), and has since been used by for example to investigate antigovernment networks (Metternich et al., 2013) and dynamic network effects in international relations (Minhas, Hoff and Ward, 2016). Unlike longer standing datasets such as Correlates of War, Militarized Interstate Disputes or Armed Conflict Location Event Data, ICEWS records not only adversarial events, but also events of neutral of positive nature, providing the opportunity to explore both positive and negative aspects of state-to-state relations.

ICEWS utilizes commercially-available news sources from 300 different publishers to extract data on interactions between political actors at the domestic and international levels. It filters the data stream to "those news stories more likely to focus on socio-political topics and less likely to focus on sports or entertainment". In the original ICEWS data, each observation codes an action (e.g., threaten, engage in diplomatic cooperation, provide economic aid) initiated by one country (source) toward another (target). All types of actions (called "issues" in the dataset) are organized in twenty top-level categories and have a corresponding "intensity score" ranging from -10 (e.g., conventional military force) to 10 (e.g., demobilize armed forces). For the purposes of this thesis, an action is called positive its intensity score is above zero, and negative otherwise.

While extremely rich, ICEWS data has several important limitations. First, the distribution of event reports is skewed to developed countries which are much more likely to be mentionaed in news reports. Thus, one may confuse cases of the absence of news reports with cases of the absence of actual events between two countries. In addition, some aspects of interactions may be too secretive to be captured by media reports, while others (such as alliances among political parties) are too constant to be considered newsworthy (Jäger, 2018). I mitigate the first concern by including sender and receiver random effects in the latentnet model (discussed in Section 4 in more detail). The second concern, fortunately, is less worrying when restricting attention to government-to-government interactions. In order to do that, I subset the data such that actors in both the source and target country fall in one of the following categories: cabinet, executive, government, legislative, ministry, military, navy, parliamentary, and police. Such subsetting retains 70% of the data, while the remaining 30% of country -to country interactions represent non government interactions, or interactions of governments with non-government entities in a foreign country. It also makes the resulting measures of country-to-country interactions more interpretable.

Additional difficulty arises from the fact that, on average, reported negative interactions are more intense than positive ones – the average value for positive action intensity is 3, but for negative intensity it is -5, making it hard to consider positive and negative interactions at the same time. Another important point to be considered is that there is a high correlation between negative and positive interactions for each country: country that initiates/receives greater numbers of positive interactions, also initiates/receives greater numbers of negative interactions. The data transformations suggested in this chapter help alleviate most of these concerns.

The goal of this thesis is to construct an informative characterization of state-to-state relations in the context of the network of international relations for a given year. The original ICEWS events are encoded with a daily frequency. In a given day, there are few state-to-state interactions between each pair of countries, and even fewer issues. Hence, I aggregate daily ICEWS data to yearly format, recording the number of interactions that occured between each pair of countries on each issue in a given year. This is a high-dimensional object as there are 230 possible issues. In addition, the data contains both positive and negative interactions. Thus, I apply several steps of data manipulation to obtain the weights that could be used in latent network analysis.

First, I split the ICEWS data for each year into two datasets - one containing only positive interactions, and one containing only negative interactions. Consider the construction of the summary of positive interactions. For each country pair, I summarize the interactions over each issue occurring in a given year by

$$I^{+}_{ijk} = \frac{n_{ijk}}{max(n_k)} * \frac{I_k}{10},$$

where I^{+}_{ijk} is the index summarizing all actions of country i toward country j on (positive) issue k, n_{ijk} is the number of actions country i took toward country j on issue k during the year, $max(n_k)$ denotes the maximum number of actions any country took toward any other country on issue k during this year, I_k is the intensity score assigned to issue k in ICEWs. As intensity is originally coded on a -10 to 10 scale, (with positive events having intensities [0.1,10]) I divide this by 10 to put it on a more intuitive 0.01 to 1 scale. Thus, the first part of the index ($\frac{n_{ijk}}{max(n_k)}$) belongs to the interval [0,1], and the second ($\frac{I_k}{10}$) to the interval [0.01,1]. Similar calculations are made for the matrix of negative interactions:

$$I^{-}_{ijk} = \frac{n_{ijk}}{max(n_k)} * \frac{I_k}{-10},$$

where each issue k has ICEWS Intensity below 0.

The I^{+}_{ijk} and I^{-}_{ijk} indexes preserve both the information about the frequency of interactions, and their direction and intensity. By normalizing both components of the index I capture the information about the frequency of an interaction relative to the maximal number of such interactions in the dataset, giving a representation of whether interacting n times over issue k is a lot or a little.

For each year of the data, the resulting indexes comprise two matrixes of size $(D \times K_+)$ and $(D \times K_-)$, where D is the number of dyads and K_+ and K_- are the number of positive and negative issues, respectively. The aim of the next step is to collapse these matrixes into vectors of length D, that provide a unidimensional measure of positive and negative interactions, respectively. In order to achieve this, I need to obtain vectors of weights that could be applied to the matrices of positive and negative interactions. I compile two matrices of issues (positive and negative) initiated by each country. The resulting matrixes are of size $K_+ \times S_+$ and $K_- \times S_-$, respectively, where K_+ is the number of positive issues, and S_+ is the number of countries (not dyads) initiating these issues. I populate the matrixes with the sum of I_{ijk} score for all sources (for positive and negative interactions): $\sum_i I_{ijk}$. Thus, each issue is represented with a row vector summarizing the frequency-weighted intensity with which source countries (column vector) initiate it. I use this matrix to perform principal component analysis. The resulting first principal component accounts for as much of the variability in the data as possible (76% in variation in S_+ matrix, 73% in variation in S_- matrix). I further use the weight each issue as assigned the first principal component and apply it to the matrix of I_{ijk} indexes. This step allows me to collapse multidimensional network of international relations into two unidimensional measures, calculating the wighted average of positive/negative interactions between each pair of states in a given year. I call the resulting measures PC_{aff} and PC_{ant}, respectively. These measures are designed to summarize direct country-to-country relations in a given year. Yet they do not capture the network nature on international relations.

One of the key features of the ICEWS data is that the affinity and antipathy measures are highly positively correlated. Thus, either measure may say as much about overall intensity of interaction as about its valence.

The simplest way to calculate the total score of the relationship would be to rely on the difference between PC_{aff} and PC_{ant}. But this approach does not account for the profile of interactions of individual countries. Moreover, it might be subject to bias, if the media accounts focus on negative (or positive) interactions for specific countries.

I propose a unidimensional measure: Affinity-Antipathy (AA) defined as the difference between the actual Affinity to the Affinity predicted by Antipathy score. That is, the residual of regression of Affinity on Antipathy of country i in year t. Positive AA suggests that the interactoin in (i, j) dyad is more positive than would be expected given the negative (i, j) interactions. This measure helps to characterize (i, j) interactions as positive of negative at the given level of "contact".

$$\text{AA} = \text{PCA-affinity} - \text{PCA-antipathy}\times$$
$$(\text{PCA-antipathy}'\text{PCA-antipathy})^{-1}(\text{PCA-antipathy}'\text{PCA-affinity})$$

Another possible alternative is to combine the S_+ and S_- matrixes and take first two Prinicpal Components. Exploring the sets of issues contributing to PC1 and PC2, I found that both sets contain positive, as well as negative issues. For example, PC1 contains both "Express accord" and "Threaten with military force". Furthermore, both issues are assigned positive weight. Similarily to the issues contributing to the first principal component, second principal component contains both positive and negative issues, sometimes entering with the same sign (for example, "Express intent to engage in diplomatic cooparetion" and "Use conventional military force" both have negative weights). Given that is is hard to interpret the measure of state-to-state interactions that results from such sets of weights, I leave this task for the future investigation.

In the following section, I briefly discuss the construction of the measure of state-to-state relations that captures direct relations in the context of the whole network of international relations using PC_{ant} and PC_{aff} as observed measures of positive and neagtive state-to-state relations, respectively.

CHAPTER 4

Latent Network Approach: Application to International Relations

In order to construct a measure of country-to-country relations that takes other international relations into account, I employ the approach to modeling networks suggested by Hoff, Raftery and Handcock (2002). I assume the existence of such a latent space of characteristics of the countries that relationships in the network form as a function of distances between these countries in the space of these characteristics as well as functions of observed dyadic level covariates. I utilise the latentnet package (Krivitsky and Handcock, 2007) to fit latent random effect models, where the probability of a network G, on a set of nodes is a product of dyad probabilities, each of which is a GLM with linear component $\eta_{i,j} = \sum_k^p \beta_k X_{i,j,k} - ||Z_i - Z_j|| + \delta_i + \gamma_j$, where X is an array of dyad covariates, β is a vector of covariate coefficients, $-||Z_i - Z_j||$ is a negative euclidean distance between nodes in thelatent space, δ_i and γ_j are sender and reciever random effetcs. I focus on a simpler case with no covariates: $\eta_{i,j} = -||Z_i - Z_j|| + \delta_i + \gamma_j$, I apply latentnet approach to 42 networks: a network of positive and negative interactions (characterized by $\mathrm{PC_{aff}}$ and $\mathrm{PC_{ant}}$, respectively) for each of 21 years of data.

The key attractive feature of these models is that the dependent variables ($\mathrm{PC_{aff}}$ and $\mathrm{PC_{ant}}$) are observed, and the position of each country in the two-dimensional latent space (for each of the variables) can be estimated as coordinates in this space. Thus I assume that the conditional expectation of $\mathrm{PC_{aff}}$ and $\mathrm{PC_{ant}}$ between two countries (constructed in Chapter 3), given the covariates, depend only on the distance between them in the respective unobserved latent space. I interpret these distances as predictors of the conditional value of interaction between two countries given the network of international relations[1].

Since ICEWS data covers the issues that can be positive (such as economic aid) or negative (such as engagement in military hostilities) in nature, I refrain from mapping them in the same network and continue to work with matrices of $\mathrm{PC}_{\mathrm{aff}}$ and $\mathrm{PC}_{\mathrm{ant}}$ relations defined earlier. For each of the networks, I estimate the model, suggested by Hoff, Raftery and Handcock (2002) based on the following assumptions:

1. The formation of ties between pairs of countries is independent, given their coordinates: $Pr(Y = y|Z) = \Pi_{(i,j)} Pr(Y_{i,j} = y_{i,j}|Z)$

where Z is a matrix with coordinates of individual node location in rows.

2. The conditional probability of tie formation (tie value) depends on the latent positions only through their conditional mean given their distance apart ($||Z_i - Z_j||$): $Pr(Y_{i,j} = y_{i,j}|||Z_i - Z_j||) = f(y_{i,j}|E(Y_{i,j}|||Z_i - Z_j||))$.

3. Conditional mean can be expressed in terms of a predictor function, $\eta_{i,j}$, and a known link function g. Since I focus on the continous response variable, I employ a link function that is identity

$$E(Y_{i,j}|||Z_i - Z_j||) = g^{-1}(\eta_{i,j}(||Z_i - Z_j||)) = \eta_{i,j}(||Z_i - Z_j||).$$

The model allows to specify sender and receiver random effects: assume country A initiates many interactions, while country B initiates interactions with a small subset of the actors receiving ties from A. Including sender and receiver random effects allow us to model A and B as "similar" even though A is more "socially active". This step is especially important, given the unequal media attention given to different countries in the ICEWs data. I can fit a model that specifies the probability of a tie existing between i and j , γ_i is a sender random

[1]Krivitsky and Handcock (2008) proposed an algorithm that implements Bayesian inference for the models based on a Markov chain Monte Carlo algorithm. It computes maximum likelihood estimates for the latent position model and implements a two-stage maximum likelihood method for the latent position model.

effect, and γ_j is a receiver random effect.

As I want to take the information about intensity and frequency of interactions into account, I apply the link function for the Gaussian distribution, which is simply the identity function, where $\mathrm{PC}_{\mathrm{aff}_{ijt}}$ and $\mathrm{PC}_{\mathrm{ant}_{ijt}}$ scores serve as an outcome variable.

I fit an ERGM model using MCMC to assess a country's coordinates in latent space, that I use to calculate the dyadic distances (see Krivitsky and Handcock (2008) for further reference) and estimate for each year t

$$\mathrm{PC}_{\mathrm{aff}_{ij}} = \beta_1 - |Z_i - Z_j| + \gamma_j + \gamma_i, \tag{4.1}$$

where $\mathrm{PC}_{\mathrm{aff}_{ij}}$ is the characterization of positive relations between country i and country j, $||Z_i - Z_j||$ is the euclidean distance between countries in two-dimensional latent space, γ_i is a receiver random effect, γ_j is the sender random effect. I apply the same procedure to the matrix of negative relations to construct the network of negative relations. The key output of ERGM model are two sets of coordinates in two latent dimensions for each country, one for positive and one for negative interactions. An example of the network of positive international relations in 2011 is presented on Figure 4.1.

As expected, countries that participate in more interactions appear closer to the center of the network while those having fewer interactions appear on the periphery. Countries that interact with the same third-party countries are closer to each other. The diagnostic plots of this network are presented on Figure 4.2.

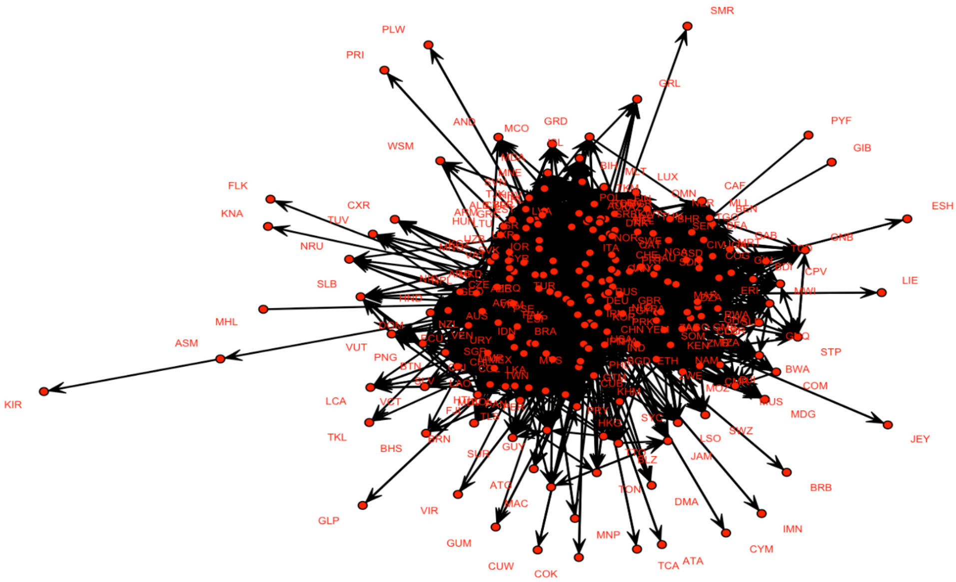

Figure 4.1: Network of Positive relations in 2011

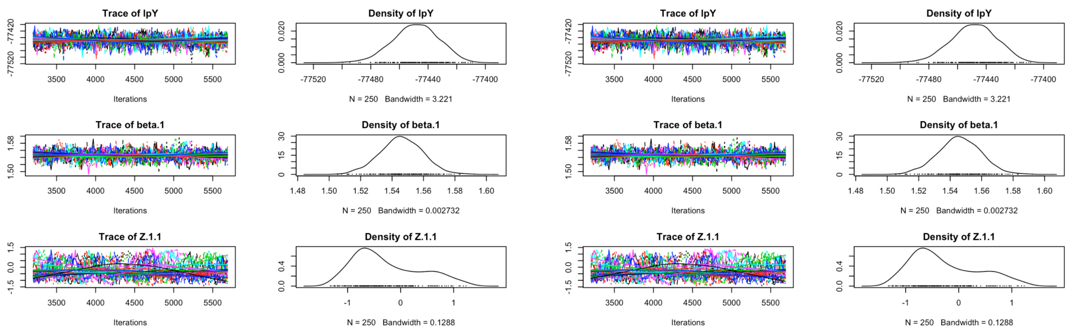

Figure 4.2: MCMC diagnostics

I assess the goodness of fit by examining how similar the networks simulated from the posterior predictive distribution are to the original for higher-order statistics of interest: distribution of in- and out- degree centralities and minimum geodesic distances (Figures 4.3, 4.4 and 4.5). I conduct this analysis via a goodness of fit formula in latentnet package.

The line represents the actual proportion of nodes with a given degree/geodesic distance observed in the data, while the boxes represent the proportion of nodes with correspoding degree/geodesic distance predicted by the model.

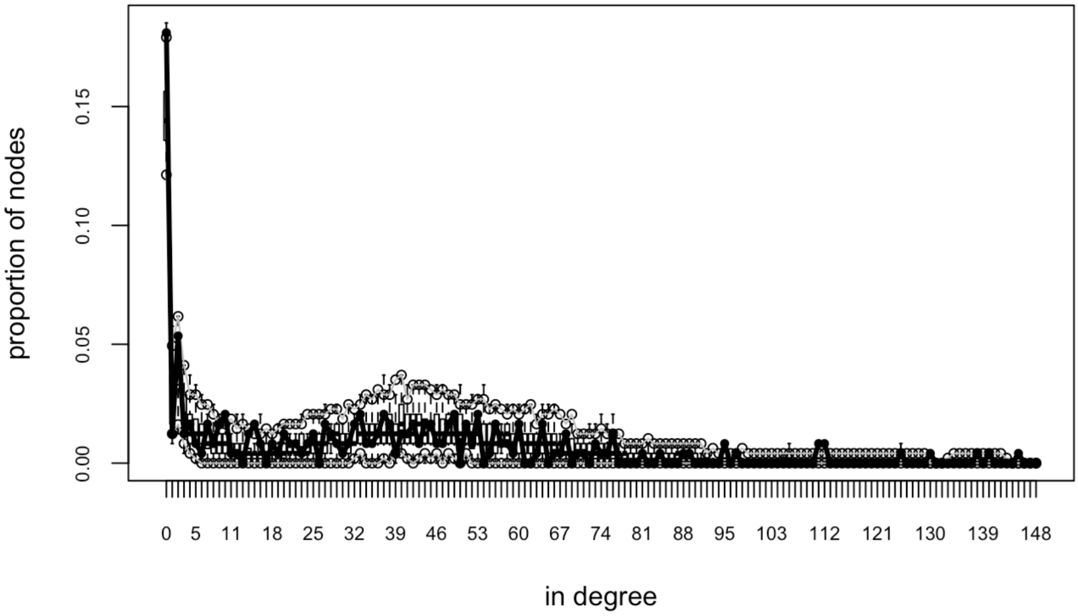

Figure 4.3: In-degree centralities: predicted and actual

On average, the model underpredicts the number of countries with one of connection directed at them (Figure 4.3).

As we can see, the model also underestimates the number of countries that initiate only one connection (Figure 4.4).

Investigating minimum geodesic distance, one can note, that, on average, the model somewhat overestimated share of countries with minimum geodesic distances of 3 and 4 compared to the data. Overall, the model demonstrates a good fit.

Each country in the dataset has 4 coordinates that characterize it's position within a network in a given year: X_+, Y_+, X_-, Y_- where X_+ and Y_+ are country's coordinates in the latent space of positive interactions, and X_- ,Y_- are country's coordinates in the space of negative interactions. Using these coordinates, we can calculate the distance between countries for each dyad. Each (negative) distance

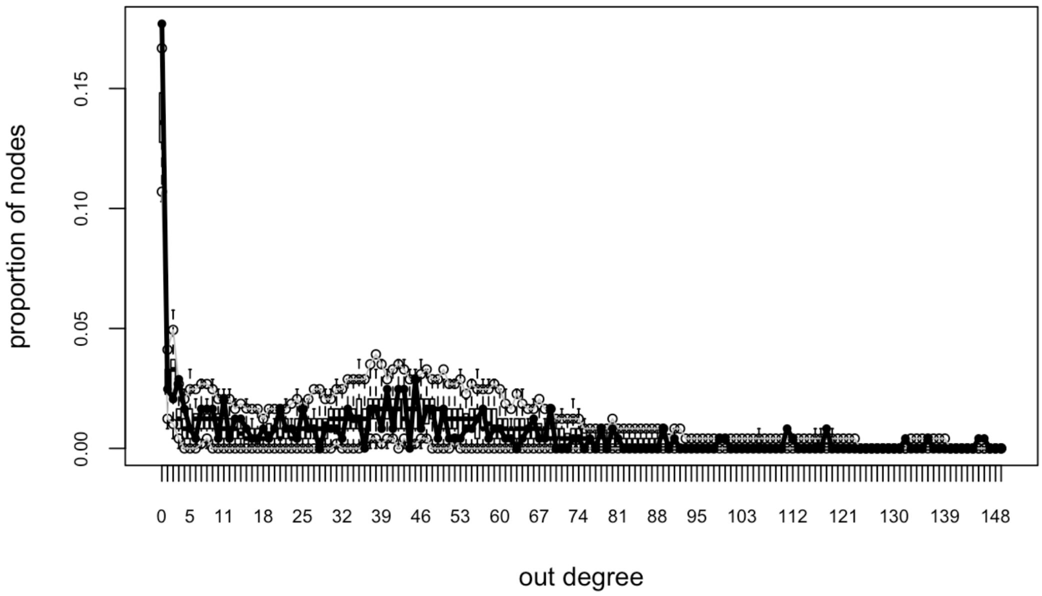

Figure 4.4: Out-degree centralities: predicted and actual

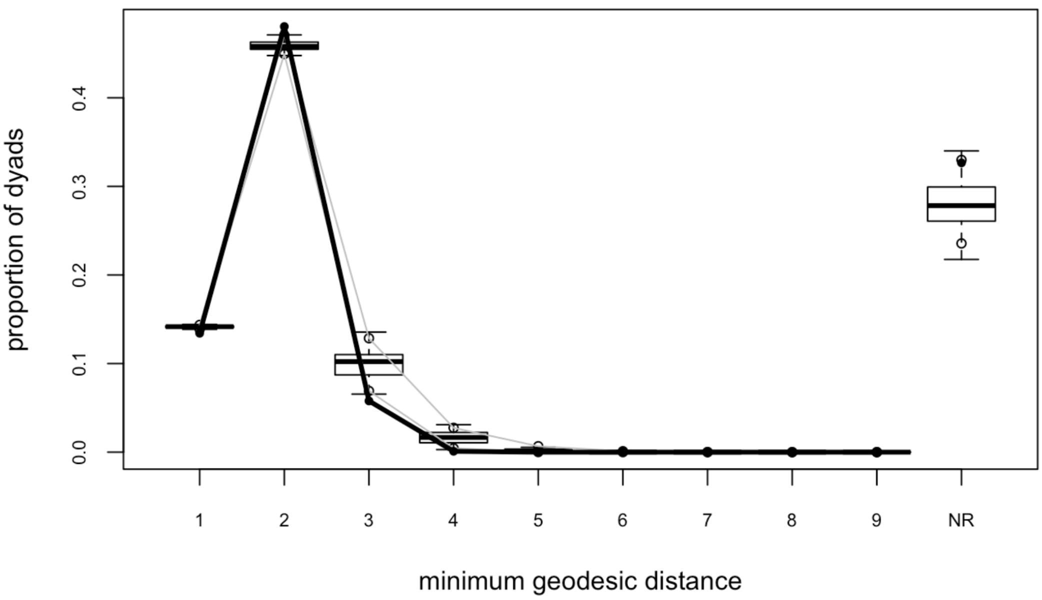

Figure 4.5: Minimal geodesic distance: predicted and actual

can be interpreted as a functon of the conditional expectation of positive or negative interactions between two countries, given all the information embedded in the network. The higher is the distance, the less likely are interactions of that type between the countries. To facilitate interpretation, we translate the distances to NetworkAffinity and NetworkAntipathy scores as negative exponentials,

$$\text{NetworkAffinity}_{ij} = exp(-||Z_i^+ - Z_j^+||)$$
$$\text{NetworkAffinity}_{ij} = exp(-||Z_i^- - Z_j^-||)$$

so that they have a straightforward interpretation: the higher is the score, the greater is the probability of interactions in positive/negative networks. These measures are defined on $[0, 1]$ interval. As in Section 3, the AA score is constructed to provide unidimensional measure of interactions for each pair of countries.

CHAPTER 5

Examining the Proposed Measures of International Relations on a Set of Cases

The proposed measures of state-to-state relations are viable to the extent to which they are useful. Before employing them to predict the volume of inernational trade, however, I examine them in a context of specific cases. This step is desirable, since, after many steps of data transformation, it is advantagetous to make sure that they are alligned with the expectations. Since each year of the data has around 41200 dyads in both Affinity and Antipathy networks, I select several individual cases for examination.

First, I consider Affinity-Antipathy profile of Russia in 2015 (Figure 5.1). The X axis represents the NetworkAntipathy score that Russia exhibits to other countries. The Y axis represnts NetworkAffinity score. They are calculated as functions of distances between countries in a social space of negative and positive relations, respectively.

Consistent with prior studies, the graph suggests positive and significant correlation between positive and negative connections. This reflects the view that the degree of affinity and antipathy depends on the amount of "contact". The regression line helps to examine to which countries Russia exhibits greater NetworkAffinity than expected from the level of NetworkAntipathy.

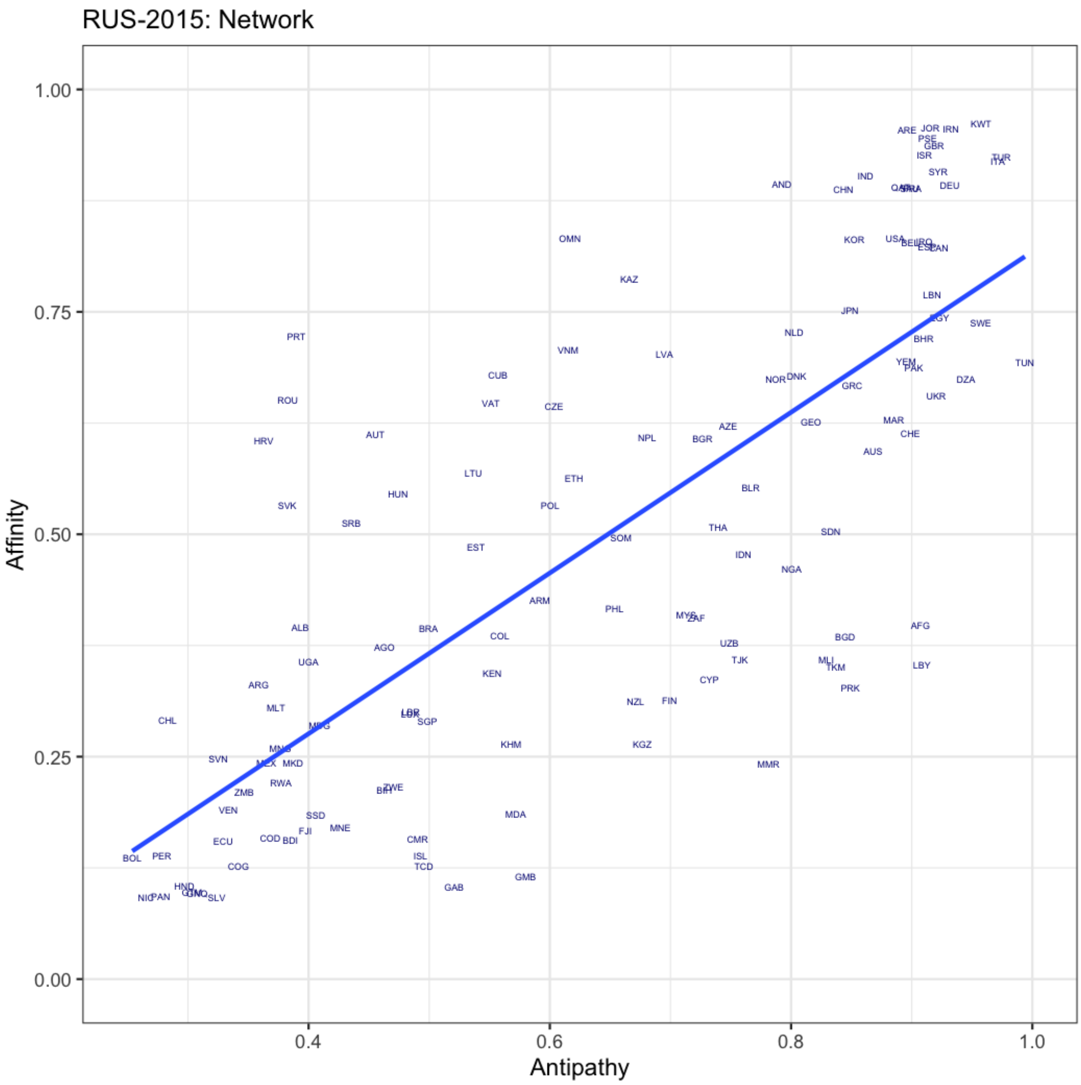

Figure 5.1: Affinity-Antipathy Profile of Russia in 2015

Consider cases of high level of "contact", where both NetworkAffinity and NetworkAntipathy scores are high. Predictably, Russia has greater than average Antipathy towards Ukraine than would be expected at the given level of contact, considering annexation of Crimea in May of 2014. As expected, Russia exhibits greater NetworkAffinity level to China, Germany. The higher than expected level of NetworkAffinity of Russia towards USA reflects the events of 2015: the signing of Minsk II accords, Vienna talks and a bilateral meeting of Obama and Putin during G-20 Summit in Turkey.

Examining the cases of low level of “contact” one can see, for instance, that Mexico and Peru experience the level of NetworkAffinity that is expected from the level of NetworkAntipathy, exhibited to them by Russia. By comparison, Chile has higher affinity levels, reflecting the fact that it signed several trade deals with Russia, helping the latter to alleviate the pressures of sanctions employed by EU countries and USA.

Next, one can examine the dynamics of network-based measures of affinity and antipathy on a different case and compare them to PCA-based measures. Consider relations of North and South Koreas. I calculte the traditional S-score (that is available untill 2000) for the whole time priod to afford comparison of proposed measures to it.

Let us first examine the PCA-based measures (Figure 5.2): PC_{ant} score captures spike in negative relations in 2010 with the ending of South Korea's Sunshine Policy, the March sinking of a South Korean naval vessel by the North, and the November attack on YeonPyeong Island. It also captures the generally worsened relations from 2010. The AA captures the improved relations in 2000 when the leaders held a summit meeting and in 2007 when the leaders signed a peace declaration as well as the generally improved relations in the period between those two.

Figure 5.2: North-South Korea Relations over time: PCA-based measures

Next, consider the network-based measures (Figure 5.3): NetworkAntipathy shows a high degree of antipathy throughout the period. Thus, while the PCA-based measure capture the immediate impact of events, the network measure captures the persistently adversarial nature of the relationship. The AA score indicates a poor relationship with little trend or direct interpretation of the small peaks and valleys in terms of the bilateral relationship.

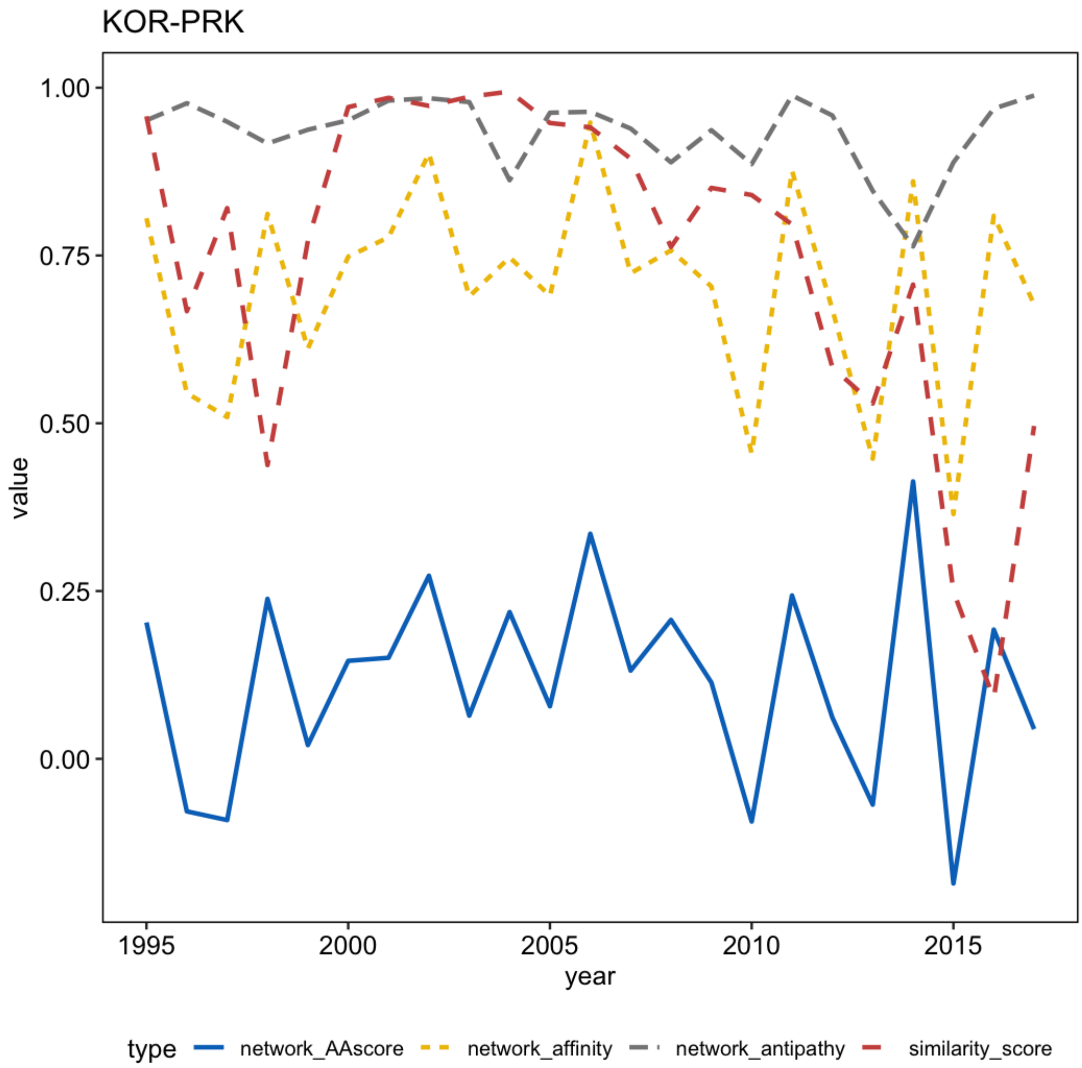

Figure 5.3: North-South Korea Relations over time: Network-based measures

Another way to examine the network-based measures is to other indicators of state-to-state relations. Since ICEWS data builds upon the events reported in the media, one can compare the measures of approval recieved by the government of one country from the citizens of the other to network-based and PCA-based measures. I utilize the Gallup World Poll data, asking the the citizens of USA about their approval of Russian and UK governments, respectively. The data covers the 2006-2015 time period. Figure 5.4 presents the juxtaposition of network-based and $\mathrm{PC}_{\mathrm{aff}}$ measures with approval ratings. We can see that network-based measures exhibit much more similar dynamics to Gallup measures of approval, while non-network summary of measures is closer to it in levels.

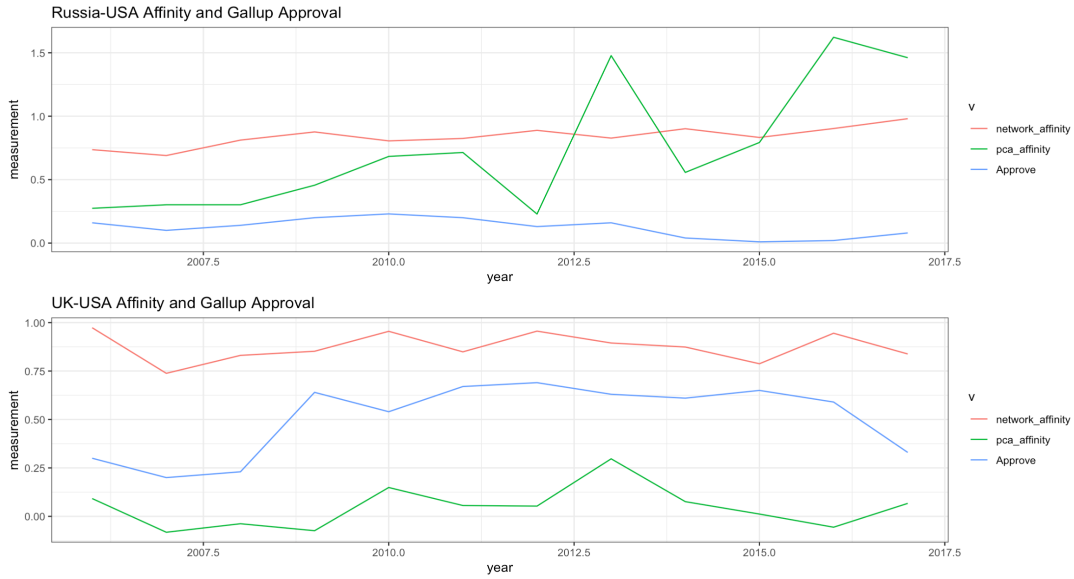

Figure 5.4: Gallup Approval and Proposed Measures of Affinity

Given these differences, it is interesting to examine the correlation matrix of Network-based and PCA-based measures alongside Gallup Approval and Disapproval ratings (Figure 5.5). Gallup Approval ratings are negatively correlated with both PC_{aff} and PC_{ant} measures, and correlate positibvely with Gallup Disapproval ratings. Both Network-based measures correlate positively with Gallup Approval and Disapproval. Network-based measures of NetworkAffinity and NetworkAntipathy are less correlated with each other than PCA-based measures of Affinity and Antipathy.

	Disapprove	Approve	network_affinity	network_antipathy	pca_affinity	pca_antipathy
Disapprove	1.00000000	-0.6572180	0.03071579	0.22589899	0.1339438	0.20713288
Approve	-0.65721798	1.0000000	0.16557180	0.22720449	-0.0994911	-0.21172285
network_affinity	0.03071579	0.1655718	1.00000000	0.39195015	0.3339967	0.12824195
network_antipathy	0.22589899	0.2272045	0.39195015	1.00000000	0.2417097	-0.02854836
pca_affinity	0.13394379	-0.0994911	0.33399670	0.24170972	1.0000000	0.73280220
pca_antipathy	0.20713288	-0.2117229	0.12824195	-0.02854836	0.7328022	1.00000000

Figure 5.5: Correlation matrix of Network-based and PCA-based measures with Gallup Approval and Disapproval

Overall, the examination of cases suggests that Network-based and PCA-based measures capture different aspects of international relations. In Section 6 I expore their applicability to predicting bilateral trade volumes and compare them to the traditional S-score.

CHAPTER 6

Predicting Trade Flows Using Network-based Measures of Country-to-Country Relations

In this chapter I employ simple gravity models to predict future trade flows between countries. International trade data was taken from CEPII database, covering 1995-2014 time period (see Head, Mayer and Ries (2010) for discussion of CEPII measures). The main variables of interest are FLOW and FLOW_0 in the original CEPII dataset, where the former is the volume of trade from the source to the target in a given year, containing many NA values. FLOW_0, on the other hand, replaces NA values with zero in cases where there is enough evidence that the missing-ness of data very very likely indicates a zero trade volume. Thus, it only contains NA or 0 values. I concatenate these variables, replacing the NA values in FLOW by values of FLOW_0, thus retaining more observations and alleviating selection bias. CEPII dataset also provides us with data on GDP per capita for source and target countries, as well as geographical distance between them. As a baseline for the comparison, I first estimate the model of trade using non-network measures of relationship in a dyad: PCA-based measures and traditional S-score. I employ the gravity model discussed in Head and Mayer (2014) of the following form:

$\log(\text{trade}_{ijt}) = \alpha_0 + \beta Z_{ijt-1} + \gamma_1 log(GDP_{it}) + \gamma_2 log(GDP_{jt}) + \gamma_3 log(distance_{ij}) + \lambda_{1ij} + \lambda_{2it} + \lambda_{3jt} + \epsilon_{ijt}$, (6.1)

where Z_{ijt-1} is a measure of interest: *S-score*, *similarity-score*, PC_{aff}, PC_{ant}, PC_{AA} or their combination in the previous year, λ_{1ij} is a dyad fixed effect,λ_{2it}, λ_{3jt} are source-year and target-year fixed effects, respectively. The results are presented in Table 6.1.

We can note, that inclusion of S-scores reduces the sample size by roughly 5 times, due to deletion of "politically-irrelevant" dyads from the data. Thus, comparison of the predictive powers of the model should be made with caution, as they are not calculated on the same sample. However, when performed on the sample restricted to the dyads for which the S-score is available, new measures still provide the improvement of adjusted R^2. One can see that S-score has no statistically significant association with trade flows in the future period. PCA-based measure AA and PC_{aff} are associated with lower trade flows in the future period, which run contrary to existing theories of inernational trade.

Let us consider the similar models with Network-based measures, presented in Table 6.2. The measures of interest are now *S-score*, *similarity-score*, *network-affinity*, *network-antipathy*, *network-AA score* or their combination in the previous year. The results show that an increase in 1 unit of network-antipathy in a previous year is associated with increase of trade flows by 0.18%, whereas the increase in NetworkAA score and NetworkAffinity by 1 unit are associated with 0.09% and 0.41% increase in trade flows, respectively. Standard errors are quite large. Yet the results are in line with expectations, given the interpretation of network measures. I conclude that network-based measures, while being less congruent with expert evaluations at first sight, appear to perform better at predicting trade flows. Traditional S-score appears to have no significant predictive power in the regressions.

	Dependent variable:				
	Log(FLOW_r0)				
	(1)	(2)	(3)	(4)	(5)
PCA affinity$_{t-1}$	-0.21^{*}		-0.21^{*}		
	(0.12)		(0.12)		
PCA antipathy$_{t-1}$		0.03	0.02		
		(0.16)	(0.16)		
PCA AA$_{t-1}$				-0.23^{*}	
				(0.12)	
S-score$_{t-1}$					0.18
					(0.15)
Source FE	+	+	+	+	+
Target FE	+	+	+	+	+
Dyad FE	+	+	+	+	+
Sender GDP	+	+	+	+	+
Reciever GDP	+	+	+	+	+
Lag(Trade Flows)	+	+	+	+	+
Log Distance	+	+	+	+	+
Observations	59,020	59,020	59,020	59,020	7,457
R^2	0.12	0.12	0.12	0.12	0.24
Adjusted R^2	0.11	0.11	0.11	0.11	0.13

Table 6.1: Predicting Trade:PCA-based measures

	Dependent variable:				
	log.FLOW_r0				
	(1)	(2)	(3)	(4)	(5)
Network affinity$_{t-1}$	0.41***		0.36***		
	(0.14)		(0.14)		
Network antipathy$_{t-1}$		−0.18***	−0.18***		
		(0.06)	(0.06)		
Network AA$_{t-1}$				0.09*	
				(0.05)	
S-score$_{t-1}$					0.18
					(0.15)
Dyad FE	+	+	+	+	+
Sender GDP	+	+	+	+	+
Reciever GDP	+	+	+	+	+
Lag(Trade Flows)	+	+	+	+	+
Log Distance	+	+	+	+	+
Observations	59,032	59,032	59,032	59,032	7,457
R^2	0.12	0.12	0.12	0.12	0.24
Adjusted R^2	−0.001	−0.0005	−0.0005	−0.001	0.13

Table 6.2: Predicting trade flows: network-based measures

CHAPTER 7

Conclusion

International political relations are hard to characterize. Important political alliances between two countries are often made with the help of other countries, international conflicts often require mediation, efforts of countries to tackle complex issues often require coordination of many states. Hence, it is important to gauge the network structure of international relations when assessing relation between any pair of countries.

This thesis proposes a way to characterise state-to-state relations in a context of the whole network of international relations in a given year applying latent network approach proposed by Hoff, Raftery and Handcock (2002) to summarized ICEWS events dataset. Under latent space framework the probability (magnitude) of a relation between countries depends on the positions of countries in an unobserved "social space." These positions are estimated within a Bayesian framework, using Markov chain Monte Carlo procedures for making inference on latent positions developed by Hoff, Raftery and Handcock (2002). I utilize the position of each country in the "social space" to infer the distances between each dyad of countries in the data and build the measures of Affinity and Antipathy between countries. I have illustrated the performance of proposed measures, together with non-network measures, on a small set of cases and found that network-based cases are better alligned with theoretical expectations.

Furthermore, I validated the resulting measure of government-to-government relations by demonstrating that they are strong predictors international trade, outperforming the most commonly used measured of state relations, known as the S-score (Signorino and Ritter, 1999). Moreover, I have shown that, unlike non-network measures, the direction of their effect is in line with theoretical expectations.

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