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Preferential Trade Agreement Networks: Proliferation and Impact

A thesis submitted in partial satisfaction
of the requirements for the degree
Master of Science in Statistics

by

Lauren J. Peritz

2015

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Abstract of the Thesis

Preferential Trade Agreement Networks: Proliferation and Impact

by

Lauren J. Peritz

Master of Science in Statistics

University of California, Los Angeles, 2015

Professor Mark S. Handcock, Chair

In recent years, there has been a proliferation of preferential trade agreements (PTAs). Through these treaties, countries agree to reduce trade barriers and open their economies to one another. Besides facilitating cooperation between member countries, PTAs also create exclusions that may harm non-members. The scholarship on trade agreements has focused on two questions: (1) when do countries join PTAs? and (2) how do PTAs impact trade cooperation? There is little consensus on answers due, at least in part, to methodological obstacles. The indirect effects of PTAs—on non-member countries—are important parts of the puzzle of whether they increase trade cooperation. Using network analysis, this paper shows that PTAs proliferate especially between small countries and active trade partners. The apparent impact of these treaties on trade is positive, once sufficient time-spans are included. By explicitly modeling indirect effects in a network, this paper reduces measurement bias and generates more accurate estimates.

The thesis of Lauren J. Peritz is approved.

Chad Hazlett

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University of California, Los Angeles

2015

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CHAPTER 1

Introduction

There has been a proliferation of preferential trade agreements (PTAs) in recent years. As of 2012, more than 250 of these agreements are in effect and dozens more are under negotiation. Nearly every country in the world has signed at least one, while some have signed more than thirty-five. PTAs have a common objective–to promote international trade–and all operate independently of the multilateral trade regime.

Through these treaties, countries agree to reduce trade barriers and open their economies to one another. While the main goal is to promote cooperation between member countries, PTAs also create exclusions that may harm non-members. The scholarship on trade agreements has focused on two questions: (1) when do countries join PTAs? and (2) how do PTAs impact trade cooperation? There is little consensus on answers due, at least in part, to methodological obstacles. The indirect effects of PTAs—on non-signing countries—are important parts of the puzzle of whether they increase trade cooperation. However, research to date has not explicitly modeled these indirect effects. Using network analysis, this paper shows that PTAs proliferate especially between small countries and active trade partners. The apparent impact of PTAs on trade is positive, once sufficient time-spans are included. By explicitly

modeling indirect effects in a network, this paper reduces measurement bias and generates more accurate estimates.

I model the factors that explain PTA formation and these treaties' effects using exponential random graph models (ERGM) and exponential random network models (ERNMs). Network models explicitly incorporate interdependence between units of analysis. Scholars have recently turned to network analysis to understand international politics (Cranmer and Desmarais, 2011; Hoff and Ward, 2004; Westveld, Hoff et al., 2011). This study builds on these efforts in three ways. First, it applies the ERGM framework to the domain of international economic cooperation where trade flows across borders necessarily link countries in indirect ways. The ERGM analysis shows that countries are more likely to form PTAs with trade partners when those partners are highly connected in the network. The pattern is most pronounced for countries within the same regions. Results suggest that smaller countries tend to form agreements with larger trade partners, possibly to improve bargaining leverage, but this behavior has diminished over time. Second, this paper uses valued ERGM models to show that new PTAs are associated with subsequent increases in trade, controlling for indirect network effects. The pattern suggests that when negative externalities from PTAs do occur, they are not widespread and easily offset. Third, it uses a new a modeling framework that explicitly captures the endogeneity of legal instruments and the economy. The ERNM analysis shows that trade agreements are not consistently associated with changes in a country's dependence upon trade. This suggests that countries are not fundamentally altering their relations with the global economy but rather redirecting their focus among trade partners.

The results touch on a broader debate about the relationship between the design of PTAs and their collective role in international cooperation (Johns and Peritz, forth-

coming). Over time, countries have increasingly included design features like dispute settlement mechanisms. This analysis finds a correlation between design features and the durability of the PTA. Rather than a race to the bottom, this trend suggests countries are forming highly legalized PTAs which in turn dominate the international legal landscape. Positing several possible explanations for the correlation, this paper points to next steps in the analysis of treaty design in the context of the PTA network.

The remainder of the paper proceeds as follows. The second section describes prevailing theories about the formation and impact of preferential trade agreements. The third section presents several statistical network models used in the analysis. The fourth section presents a network analysis of PTAs with particular attention to regional patterns, determinants of PTA formation, and the consequences of these treaties for international trade cooperation. The final section discusses the findings and concludes.

CHAPTER 2

PTAs and Trade

2.1 Background

Countries form preferential trade agreements in order to improve access to each others' markets. These treaties restrict the trade policies of member countries. By restricting the sorts of trade barriers countries can use, PTAs allow members to more freely exchange goods and services between their markets. That is, PTAs tend to *liberalize* the trade policy of member countries.

Trade agreements constrain or eliminate trade barriers in a variety of ways. PTAs may place an upper limit on tariffs, restrict countervailing duties and anti-dumping measures, or constrain other practices like government procurement. Many PTAs establish a free trade area where countries eliminate trade barriers on each others' products. For example, Canada, Mexico, and the United States have agreed to do so through the North American Free Trade Area (NAFTA). Some create even deeper forms of international cooperation. For example, customs unions like the Andean Community eliminate internal trade barriers and set common tariffs for non-member countries. Others even establish a common currency (monetary union). The European Union is one such example. Many have provisions for dispute settlement and

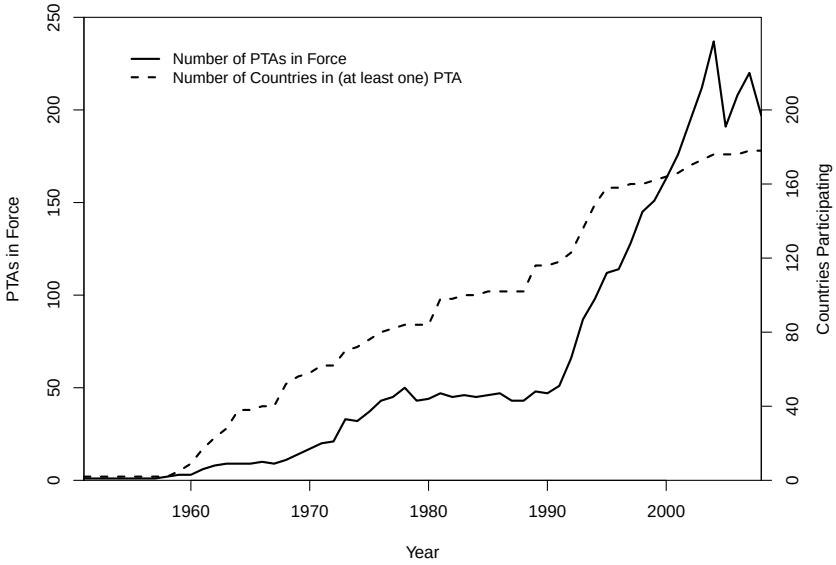
this is thought to aid in enforcing the treaty terms. Regardless of the particular form, PTAs have the common goal of promoting trade among member countries.

The motives for forming PTAs differ somewhat from one country to the next. Countries with smaller economies can benefit from establishing legal ties to larger economies (Büthe and Milner, 2008; Panagariya, 2002). For example, Singapore has formed separate bilateral treaties with China, India, Japan, and the United States. Countries with larger economies benefit from the agreements too. In many instances, countries use PTAs to link trade concessions to other issues like security or human rights or establish ties to rapidly growing markets (Hafner-Burton, 2005, 2013; Mansfield and Pevehouse, 2000). Some scholars argue that countries often form trade agreements with one another to improve their economic leverage against a larger trade partner (Lukauskas et al., 2013). For example, through the MERCOSUR agreement, many of the South American countries banded together to gain bargaining power when interacting with the United States. While the reasons countries have for forming PTAs are varied, one clear trend emerges.

Preferential trade agreements have multiplied in the last few decades. As shown in Figure 2.1, a small number of PTAs were formed during the 1960's through 1980's. In the 1990's the number of new PTAs increased dramatically. At the same time, the number of countries participating in at least one PTA has increased. As more countries enter the network of PTAs they have formed not just one but many treaties with trading partners and the network has become substantially denser.

This paper considers the causes and consequences of the complex network of preferential trade agreements. Many economic and political factors have been used to explain PTA formation. Some scholars have speculated about the impact of PTAs on international cooperation more broadly. Do PTAs increase trade in meaningful ways?

Figure 2.1 – Proliferation of Preferential Trade Agreements Over Time



Do they reduce the risk of trade conflicts between countries? I test these questions empirically using network analysis.

2.2 Theory

2.2.1 Network Structure

Countries form preferential trade agreements to secure trade relations with one another. These agreements bring benefits to member countries including cheaper goods for consumers, reliable markets for producers, and assurances of future economic stability. But PTAs are not formed in a vacuum; part of countries' motivation for creating these agreements comes from the broader trade environment (Bhagwati and Panagariya, 1996; Mansfield, 1998). This environment is shaped by existing PTAs which have externalities—that is, they impact non-member countries. To explain pro-

liferation, one should account for externalities. Network analysis is an appropriate statistical tool to do so.

When countries enter into a PTA, they lower prices which in turn shifts demand across exporters, diverting trade from non-members (Panagariya, 2000).[1] As a result, non-member countries may experience a negative impact from PTAs in the form of relative trade losses. They have an incentive to acquire preferential trade terms as well to get the same advantages. These countries may (1) join existing PTAs or (2) form separate agreements with other countries. In both instances, countries benefit from PTAs. To the extent that PTAs confer benefits to members and disadvantages to non-members, they should proliferate over time.

There are costs to both expanding an existing PTA and forming a new one. First, current members may be reluctant to expand a treaty. Insofar as PTAs confer competitive advantages to members, members should want to maintain an exclusive treaty and not admit new countries. They should only expand membership when the prospective gains from expanding the market outweigh the costs from losing the competitive advantage. Second, forming a new PTA is costly to prospective members. Countries may incur diplomatic costs via international concessions or domestic political costs. For instance, if a domestic interest group objects to a potential trade agreement, that group can generate political pressure. Thus countries should only form new PTAs when the prospective gains outweigh these international and domestic costs. Given the various benefits and costs, theory is unclear as to which tendency should dominate—expanding existing agreements or forming new ones.

Moreover, existing trade flows should affect a country's decision to form a PTA. On one hand, countries may use treaties to reinforce existing trade relations, effectively

[1] It need not be a zero-sum game but most models predict some sort of diversion.

codifying a practice already in place. Accordingly, countries should create treaties with their most important trade partners. On the other hand, countries may use PTAs to *expand* trade with new partners, using law to advance economic interests. Does the volume of trade between two countries increase or decrease the likelihood that they form an agreement? To empirically answer this question, one should account for the indirect relationships by modeling trade flows between a potential PTA member and its other trading partners.

2.2.2 Economic and Political Factors

Some theories of international trade predict that countries with smaller economies will have stronger incentives to form trade agreements (Krugman and Obstfeld, 2000). Smaller economies tend to have less leverage in international affairs: their ability to retaliate through trade barriers, sanctions, and other means will have only modest impacts on target countries. In a similar vein, they will also be the most vulnerable when other countries impose trade barriers. These countries will, on average, be more likely to seek secure trade relations with other countries through PTAs.

Smaller countries tend to have less diversified economies and hence rely more heavily on international exchange of goods and services. This highlights another important predictor of PTA formation: trade dependence. When the value of imports and exports is large, relative to a country's gross domestic product, we say a country is highly trade dependent. A country that is highly trade-dependent may be especially motivated to form PTAs in order to ensure future stability in trade relations. In both instances, countries may offer inducements to potential PTA partners. For example, they may agree to treaty terms that are especially favorable to partners, including linking trade to other non-trade issues like security or human rights. All else equal,

countries with smaller economies or which rely more heavily on trade will be more likely to form PTAs.

PTAs have different design feature; one of the most important is whether they has provisions for settling disputes. Dispute settlement mechanisms (DSMs) are intended to facilitate peaceful resolution of conflicts between member countries. Ideally, DSMs provide a quasi-judicial venue for countries to investigate possible treaty violations, receive judgments from an impartial third party, and agree to a plan for resolution. DSMs are though to stabilize the trade agreement by reducing the chance that countries find themselves in an irreparable conflict and abandon the PTA altogether. Accordingly PTAs with dispute settlement mechanisms should be more durable over time.

While common on paper, these dispute settlement mechanisms are rarely used.[2] If they go unused, are they really stabilizing PTAs? Political scientists have offered various explanations for why DSMs are so frequently included in trade agreements. Some have suggested a deterrent effect. When countries face legal recourse for violating their trade commitments, they tend to comply more. Countries choose to include the DSM to improve compliance. By deterring violations, DSMs may help the agreement last over time. Others have suggested a selection mechanism. Countries that are more committed to long-term trade cooperation are likely to form a PTA with a dispute settlement mechanism. These same countries are less likely to abandon the PTA at a later date. So DSMs may be a marker for already-stable trade agreements. Whether deterrence or selection is at work, DSMs should be associated with long-lasting PTAs.

[2]NAFTA is one noteworthy exception.

At the domestic level, preferential trade agreements make rich political fodder. Trade policy is often the source of controversy between different interest groups, depending on whether the group tends to benefit or suffer from trade liberalization. Groups that benefit from trade liberalization often support PTAs while groups that suffer from the increased foreign competition oppose them. For example, in an effort to stave off competition, the US auto industry has opposed trade agreements that reduce tariffs on foreign automobile imports. It is common for these kinds of domestic industry groups to oppose a new PTA and use their political clout to obstruct its formation.

Controversy over trade agreements is often hashed out through partisan competition or disagreements between different branches of government (Martin, 2000). Some politicians may be particularly sensitive to industry preferences. For example, legislators from Michigan might be more responsive to auto-industry preferences. These preferences enter into the political process. The more actors within government, the more opportunity for politics to generate obstacles. Scholars have referred to these divisions within government as "veto points" (Tsebelis, 1995, 2003). They have devised veto point scores that capture (1) institutional constraints like divided government and (2) partisan constraints like political opposition parties. Domestic veto points are widely thought to obstruct PTA formation (Mansfield and Milner, 2012; Mansfield, Milner, and Pevehouse, 2007; Milner and Rosendorff, 1997). The more veto points in domestic government, the less likely a country is to form a preferential trade agreement.

2.2.3 Consequences

When countries form PTAs, their main stated goal is to expand trade. For example, the United States is currently negotiating a major multilateral trade deal with several Pacific countries. The Office of the US Trade Representative states: "The Trans-Pacific Partnership will grow trade...[it] will boost U.S. economic growth, support American jobs, and grow Made-in-America exports to some of the most dynamic and fastest growing countries in the world."[3] If these intentions are borne out, then a PTA should be associated with subsequent increases in trade between member countries. Bilateral trade between members should increase in the years after signing a PTA, controlling for trade with non-members.

Trade dependence is an important part of the puzzle because it helps to identify potential externalities from PTAs. Suppose after forming a PTA, a country's trade volume with other members increases. And suppose the country's dependence on trade—the trade volume as a share of GDP remains fixed. Then the gain in trade with members was accompanied by some measurable loss in trade with non-members. Trade has been diverted: expansion of trade with PTA members implies contraction of trade with non-members. Now instead let trade dependence increase. A greater portion of a country's economy comes from international commerce. Expansion of trade with PTA members does not lead to loss in trade with non-members. There is little diversion of trade away from non-members.

Diversion points to a possible mechanism for PTA proliferation. When trade agreements are followed by the rerouting of trade from non-members to members, the non-members have incentive to secure more favorable trade relations. They may

[3]See: `https://ustr.gov/tpp`.

aim to join existing PTAs or form new ones. The creation of preferential trade agreements may be a self-reinforcing process. Conversely, when trade agreements are followed by little trade diversion, there is less incentive for non-members to take action. They may be less likely to join PTAs or form new ones. The proliferation of PTAs is not self-reinforcing. While these causal mechanisms cannot be inferred from observational data in this study, it is worth probing the plausibility of a self-reinforcing process. Trade diversion also lends insight into the implications of the PTA network for multilateral trade cooperation. Some scholars argue that in sum, PTAs hinder cooperation by creating a set of overlapping—and sometimes contradictory rules—that undermine free trade (Bhagwati, 2008). Rather than expanding net trade through common multilateral rules, PTAs reroute trade through exclusive terms and incentivize other countries to follow suit, further degrading multilateralism.

CHAPTER 3

Network Models

Network analysis is a particularly suitable statistical method for modeling the determinants and consequences of preferential trade agreements. Traditional statistical approaches assume stable unit treatment value: the outcome of a given individual unit is not influenced by the treatment status of *other* units. In many cases, this assumption is difficult to justify. Network analysis explicitly models dependence between units. The treatment state of one unit affects the treatment state of another unit. Network analysis enables one to model these spillovers. Further, the structure of the network can be used to explain treatment states. By accounting for the dependencies among units and the global structure, network analysis enables more accurate estimation and thereby inferences about the phenomena of interest.

3.1 Exponential Random Graph Models

This paper adopts three classes of network models. The first and fundamental one is the exponential-family random graph model (ERGM) which considers the network conditional on a series of predictor terms (Erdos and Renyi, 1959; Frank and Strauss, 1986; Hunter and Handcock, 2006). Predictors—network statistics—represent configurations of ties (for example, triangles of three nodes with common attribute) that

are hypothesized to occur more often than expected by chance. These terms, with their coefficients, define the probability of each edge and the probability of the entire network. A trivial example is the homogeneous Bernoulli model. The configuration is an edge, the predictor is the total number of edges, and the network may be viewed as a collection of independent and identically distributed Bernoulli random variables (Morris, Handcock, and Hunter, 2008, p.2). Now suppose we want to model an empirical case where not all nodes are equally likely to form edges with each other and not all configurations are equally likely. By running more sophisticated ERG models, we can obtain maximum likelihood estimates that describe the impact of local selection forces, including node and edge attributes, on the global structure of a network.

To model more sophisticated networks, the ERGM specification is as follows. Let the random matrix Y represent the $n \times n$ adjacency matrix of a network (with realization y) and let $\mathcal{N}(x)$ denote its support – the set of all obtainable networks as a function of the nodal variates. This is written as $\mathcal{N}(x) = y \ : \ (y, x) \in \mathcal{N}$. Further let X be an $n \times q$ matrix of covariates. Then the exponential random graph model may be written as:

$$P(Y = y \,|X = x; \eta) = \frac{\exp(\eta \cdot g(y, x))}{c(\eta;\ \mathcal{N}(x), x)}, \quad y \in \mathcal{N}(x) \tag{3.1}$$

where η is the vector of model parameters, $g(y, x)$ is a vector valued function of model statistics for the network, and $c(\eta;\ \mathcal{N}(x), x)$ is a normalizing constant.

The vector of network statistics $g(y, x)$ can include any number of structural network statistics y and covariates x that describe characteristics of the nodes and edges. For example, $g(y)$ could be a very simple network statistic like edge count, the number of edges present in the network. In an undirected network of three countries,

where only two have a preferential trade agreement with each other, the edge count is one. We can add covariates x to the vector of network statistics $g(y, x)$ which further predict the likelihood of a particular network configuration. For example, if countries i and j out of the three share a common geographical border, covariate x is a 3×3 matrix with the ij and ji elements equal to one and all other elements zero. Common borders may increase the likelihood that countries form a trade agreement. The edge count and the common geographical border can then be used to explain the particular configuration of the trade agreement network.

The model parameters η are coefficients for the network statistics $g(y, x)$. As with standard maximum likelihood estimation, ERGM parameters η are those which maximize the likelihood of obtaining the observed network from the set of all possible networks. The normalizing factor is the summation over the sample space $\mathcal{N}$ (i.e. all possible networks Y having covariates X), written as $c(\eta;\ \mathcal{N}(x), x) = \sum_{x \in \mathcal{N}} \exp(\eta \cdot g(y|x))$. Estimating this normalizing factor is one computational challenge in ERG models. I use the "`ergm`" package in `R` to estimate the models below (Hunter et al., 2008).

One key extension of the core ERG model is the generalization to valued networks. Here, edges in the network are not simply binary; they can modeled as counts or continuous variables. Krivitsky (2012) present a theory and computational methods for valued exponential random graph models. A key distinction between binary ERGMs and valued ERGMs is the inclusion of a non-binary reference distribution in the latter. This reference measure enters into the probability function and the normalizing constant in the form of a multiplier and as a constraint on the support space. The reference measure denotes the distribution relative to which the exponential form is specified. For valued networks of count data, an appropriate reference measure

could be a Poisson-reference or a geometric reference, depending on the structure of the data. For valued networks of continuous data, an appropriate reference measure could be instead Gaussian, with further modifications to the ERGM specification. These models are discussed in detail by Krivitsky (2012) and Krivitsky and Butts (2013) and implemented with the "`ergm.count`" package in `R`.

3.2 Temporal Exponential Random Graph Models

Networks can change over time, and this process is not captured by the static ERGM. Statisticians have developed dynamic network models to better account for the process. The second class of models I adopt is the temporal ERGM for modeling discrete relational dynamics. Temporal ERG models consider a sequence of observed networks over multiple discrete periods of time. In this application, the network of preferential trade agreements is observed at five-year intervals, a reasonable periodicity for the questions of interest.

I adopt a discrete time dynamic network model in which the network at time $t+1$ is a single draw from an ERGM conditional on the network at time t (and possibly previous periods) (Hanneke and Xing, 2007; Hanneke et al., 2010). The one-step transition probability from y^t to y^{t+1} is defined as:

$$P(Y^{t+1} = y^{t+1} \,|Y^t = y^t; \eta) = \frac{\exp(\eta \cdot g(y^{t+1}, y^t))}{c(\eta, y^t)}, \quad y^{t+1}, y^t \in \mathcal{Y} \tag{3.2}$$

and the normalizing constant is, similar to above, $c(\eta, y^t) = \sum_{y \in \mathcal{Y}} \exp(\eta \cdot g(y^{t+1}, y^t))$. Temporal ERGMs (TERGMs) are therefore a natural elaboration of the traditional ERG framework and are essentially stepwise ERGMs in time.

The difficulty is that in each time step, the network is changing in two ways simultaneously. To see this, begin with a Bernoulli model of network where all ties are equally likely. The ties present in the next period are a function of the rate at which new ones form (incidence) and the rate at which existing ties dissolve (reciprocal of duration). The faster ties form, the more that will be present in the next period. Conversely, the faster ties dissolve, the fewer that will be present in the next period. Change over time can thus be disaggregated in two separate processes: incidence and duration (Krivitsky and Handcock, 2013; Krivitsky and Goodreau, 2014).

Separable temporal ERG models decompose change over time into these two processes: one underlying relational formation and the other underlying relational dissolution. They assume formation and dissolution of ties occur independently from each other within each time step and model each half of the process modeled as an ERGM.

Krivitsky and Handcock (2013) describe separable TERGMs as follows. We want to model the evolution of a network Y^t at time t to a network Y^{t+1} at the next period $t+1$. Define two intermediate networks, the formation network Y^+ consisting of the initial network with ties formed during the time step and the dissolution network Y^- consisting of the initial network with ties dissolved during the time step. Let y^+ and y^- denote particular realizations of the formation and dissolution networks. The cross-sectional network at time $t+1$ is then constructed by applying the changes in Y^+ and Y^- to y^t. If Y^+ is conditionally independent of Y^- given the initial network Y^t then the dynamic model is the product of the probabilities of the formation and dissolution models:

$$P(Y^{t+1} = y^{t+1} \mid Y^t = y^t; \eta) = P(Y^+ = y^+ \mid Y^t = y^t; \eta) P(Y^- = y^- \mid Y^t = y^t; \eta). \quad (3.3)$$

Within this model we can write the two parts of the generative mechanism. Let some $\mathcal{Y}^+(y^t) \subseteq \{y \in 2^{\mathrm{Y}} : y \supseteq y^t\}$ be the sample space of the formation networks starting from y^{t-1}. Let $\mathcal{Y}^-(y^t) \subseteq \{y \in 2^{\mathrm{Y}} : y \subseteq y^t\}$ be the sample space of the dissolution networks. Given y^t, a formation network Y^+ is generated from an ERGM controlled by formation parameters η^+ and formation statistics $g^+(y^+, x)$ conditional only on adding ties. Similarly, a dissolution network Y^- is generated from an ERGM controlled by dissolution parameters η^- (which can be different) and dissolution statistics $g^-(y^-, x)$ conditional only on dissolving ties from y^t.

$$P(Y^+ = y^+ \mid Y^t; \eta) = \frac{\exp(\eta^+ \cdot g^+(y^+, x))}{c(\eta^+, x, \mathcal{Y}^+(Y^t))}, \quad y^+ \in \mathcal{Y}^+(y^t). \quad (3.4)$$

$$P(Y^- = y^- \mid Y^t; \eta) = \frac{\exp(\eta^- \cdot g^-(y^-, x))}{c(\eta^-, x, \mathcal{Y}^-(Y^t))}, \quad y^- \in \mathcal{Y}^-(y^t). \quad (3.5)$$

For each part, the normalizing constant $c(\eta, x, \mathcal{Y}(Y^t))$ is again the summation over the space of possible networks on n nodes, $\mathcal{Y}$. Below, I estimate the separable temporal ERGMs using the "`tergm`" package in `R` (Krivitsky and Goodreau, 2014).

3.3 Exponential Random Network Models

The third class, exponential-family random network models (ERNM) is an entirely novel approach developed by Fellows and Handcock (2012). Rather than taking characteristics of the nodes as fixed and modeling the network as conditional on these

characteristics, ERNMs treat the network and the characteristics as jointly responsive to one another. That is, ERNMs capture the joint relation between the process of tie selection and nodal variate influence in a cross-sectional network. Thus these models explicitly represent the endogenous nature of the relational ties and nodal variables.[1] They present an advance in network modeling by joining the process of tie selection and nodal variable influence into a co-occurring phenomena with ties affecting nodal variates and vice versa.

To capture the joint process, ERNMs combine the ERGM specification and Random Field modeling. Fellows and Handcock (2012) describe the specification is as follows. Let Y be an n by n matrix whose entries $Y_{i,j}$ indicate whether subject i and j are connected, where n is the size of the population. Let X be an $n \times q$ matrix of nodal variates. Define the network to be a random variable (Y, X) and the set of possible networks of interest in the sample space of the model is $\mathcal{N}$. The joint exponential family model for the network is:

$$P_\eta(X = x,\ Y = y|\eta) = \frac{\exp(\eta \cdot g(y, x))}{c(\eta,\ \mathcal{N})}, \quad (y, x) \in \mathcal{N} \tag{3.6}$$

where η is a vector of parameters, g is a $q-$vector valued function, $g(y, x)$ is a $q-$vector of network statistics and $c(\eta, \mathcal{N})$ is a normalizing constant so that the integral of P over the sample space of X and Y is 1. The model parameter space is $\eta \in \mathbb{R}^q$. Let $(N, \mathcal{N}, P_0)$ be a finite measure space with reference measure P_0. A probability measure $P(X = x,\ Y = y|\eta)$ is an ERNM with respect to this space if it is dominated by P_0 and the derivative is:

[1] With network-behavior panel data, it may also be possible to statistically separate the effects of selection from those of influence.

$$\frac{dP_\eta(X = x,\ Y = y|\eta)}{dP_0} = \frac{\exp(\eta \cdot g(y, x))}{c(\eta,\ \mathcal{N})}, \quad (y, x) \in \mathcal{N}$$

where

$$c(\eta, \mathcal{N}) = \int_{y,x \in \mathcal{N}} \exp \eta \cdot g(y, x) \cdot dP_0(y, x) \tag{3.7}$$

is a finite normalizing constant.

This is the joint modeling of Y and X. The model can be decomposed into two constituent processes: ERGMs and Random Fields. The first is the ERGM for the network conditional on nodal attributes. The second is an exponential family for the field of nodal attributes conditional on the network. Specifically, let $\mathcal{N}_x = y : (x, y) \in \mathcal{N}$ and $\mathcal{N}_y = x : (x, y) \in \mathcal{N}$. We can write the two constituent models as:

$$\text{ERGM}: \qquad P(Y = y|X = x; \eta) = \frac{\exp \eta \cdot g(x, y)}{c(\eta; x)}, \qquad y \in \mathcal{N}(x) \tag{3.8}$$

$$\text{Random Field}: \qquad P(X = x|Y = y; \eta) = \frac{\exp \eta \cdot g(x, y)}{c(\eta; y)}, \qquad x \in \mathcal{N}(y) \tag{3.9}$$

Further, the ERNM model in equation 3.6 can be expressed as:

$$P(X = x,\ Y = y|\eta) = P(Y = y|X = x|\eta)P(X = x|\eta) \tag{3.10}$$

where

$$P(X = x|\eta) = \frac{c(\eta; \mathcal{N}(x), x)}{c(\eta, \mathcal{N})}.$$

This model is the marginal representation of the nodal attributes. The decompositions shown above demonstrate why the joint modeling of Y and X via ERNM is different than the conditional modeling of Y given X via ERGM, as in Section 3.1. ERNM models are estimated with the new `R` package "`ernm`" by Fellows (2012); Fellows and Handcock (2012). It is not yet publicly released on `CRAN` but available from the author.[2]

[2]Please see: `http://www.fellstat.com`.

CHAPTER 4

Network Analysis of PTAs

4.1 Data

Data on preferential trade agreements are from the World Trade Organization's reciprocal trade agreement database and from Mansfield and Milner (2012). I consider the presence and absence of PTAs among all countries in international system between 1970 and 2005, observed at 5-year intervals. These data are assembled in two ways. First, I look at each period and record whether the countries formed a PTA in the previous five years. This includes instances where countries join existing PTAs, thereby expanding the membership, and cases where countries create entirely new PTAs. These data are used in most model specifications. Second, I look at each period and record whether or not the country pairs have any PTA in place. This includes PTAs formed recently or as far back as the 1950's when countries first began creating these treaties. If the countries had a PTA but it expired, then they are coded as not having a tie in the subsequent periods. These data are used in the separable temporal ERGMs. In both versions, the data are formatted into separate adjacency matrices for each time period. Countries ("nodes") are connected by PTAs ("edges" or "ties").

The analysis is restricted to *reciprocal* trade agreements in force. A trade agreement is reciprocal if it binds all member countries to the same terms. Asymmetric agreements are also common but not the focus of this analysis. Once a country ratifies a treaty, it must ensure the agreement enters into force, according to domestic legal procedures that vary from one country to the next. (Sometimes, the treaty enters into force automatically and requires no further legal action by the member countries.) Because the treaty has no binding legal authority until it enters into force, this analysis focuses exclusively on fully enacted PTAs.

Economic data enter the analysis. I include data on bilateral trade between the two countries in the indicated year. Because this analysis uses undirected networks, I consider average bilateral trade between each country pair (i.e. average of A to B and B to A). Trade data come from the United Nations Comtrade Database and are in logged units (UnitedNations, 2013). In most instances, these data enter the model as a covariate of interest. There are two exceptions. In one specification, I use bilateral trade flows to form a valued network. Bilateral trade, not the PTA, is the outcome of interest. In another specification, I calculate the five-year change in bilateral trade flows and use these changes to form a valued network. Annual data on each country's gross domestic product (GDP) and trade dependence (measured by total trade as a percentage of GDP) both come from the World Development Indicators database (WorldBank, 2013). Each of the variables receives one, two, and three-year lags when I evaluate the potential for temporal delays.

I also account for certain political factors. First, I include information about whether the PTA had a dispute settlement mechanism, a particularly important design feature. This is coded as a dummy variable. Second, I consider domestic political constraints that are thought to influence a country's decision to join a PTA. Domes-

tic veto points indicate the political obstacles a government may face in trying to join a PTA. This variable is continuous and bound between 0 and 1 with a larger number indicating more constraints. The "veto points" data come from the Political Constraint Index Dataset (Henisz, 2002), a widely-accepted source.

4.2 Visualizing the Network

The network has 110 countries (nodes), some of which are connected to one another via PTAs (edges). Because I observe the network at many points over a 40-year period, I restrict the analysis to countries that were in existence for the entire time-frame (and for which data on bilateral trade flows are available).[1] Figure 4.1 displays the network of new PTAs formed in each period, plotted over a map of the globe. For example, the PTA network denoted "PTA.1995" is the network of treaties formed between 1991 and 1995.

Throughout the 1970's, only a small number of countries formed preferential trade agreements. Most of the activity was through the formation of intra-regional, multilateral agreements. Many countries in sub-Saharan Africa secured agreements with one another. To the extent that inter-regional PTAs were formed, they tended to feature neighboring geographical regions. For example, many of the edges in the network appear between Eastern European and Western European countries. These same regional patterns appear throughout the 1980's as East and South Asian countries enter the PTA network.

[1] Countries are identified in Appendix A. One notable exclusion is Russia. The disintegration of the USSR expanded the number of countries. One important extension of the analysis will model countries' entry and exit from the PTA network.

Two types of network structures are prevalent. First, there are clusters wherein all countries in a group share edges with all others in that group. This can be observed, for example, with the Sub-Saharan African countries which in 1981 formed the PTA that became Common Market for Eastern and Southern Africa (COMESA). Second, there are k-stars where a new country enters an existing cluster and forms new ties with each member of that group. This can be observed with the Western European countries as the European Free Trade Area (now the European Union) expanded.

After 1990, the pace of PTA formation accelerated. The graphs for 1995, 2000, and 2005 show very dense networks with many countries forming multiple PTAs both within and across geographical regions. No geographical region remains uninvolved and many become highly integrated with one another. By 2005, we observe multiple ties between countries of different regions. For example, the United States, which for previous decades stood on the sidelines of the PTA network, entered agreements with countries in Western Europe, Central America, East Asia, Latin America, and the Middle East.

Figure 4.1 – Preferential Trade Agreement Network with Geography (1965-2005)

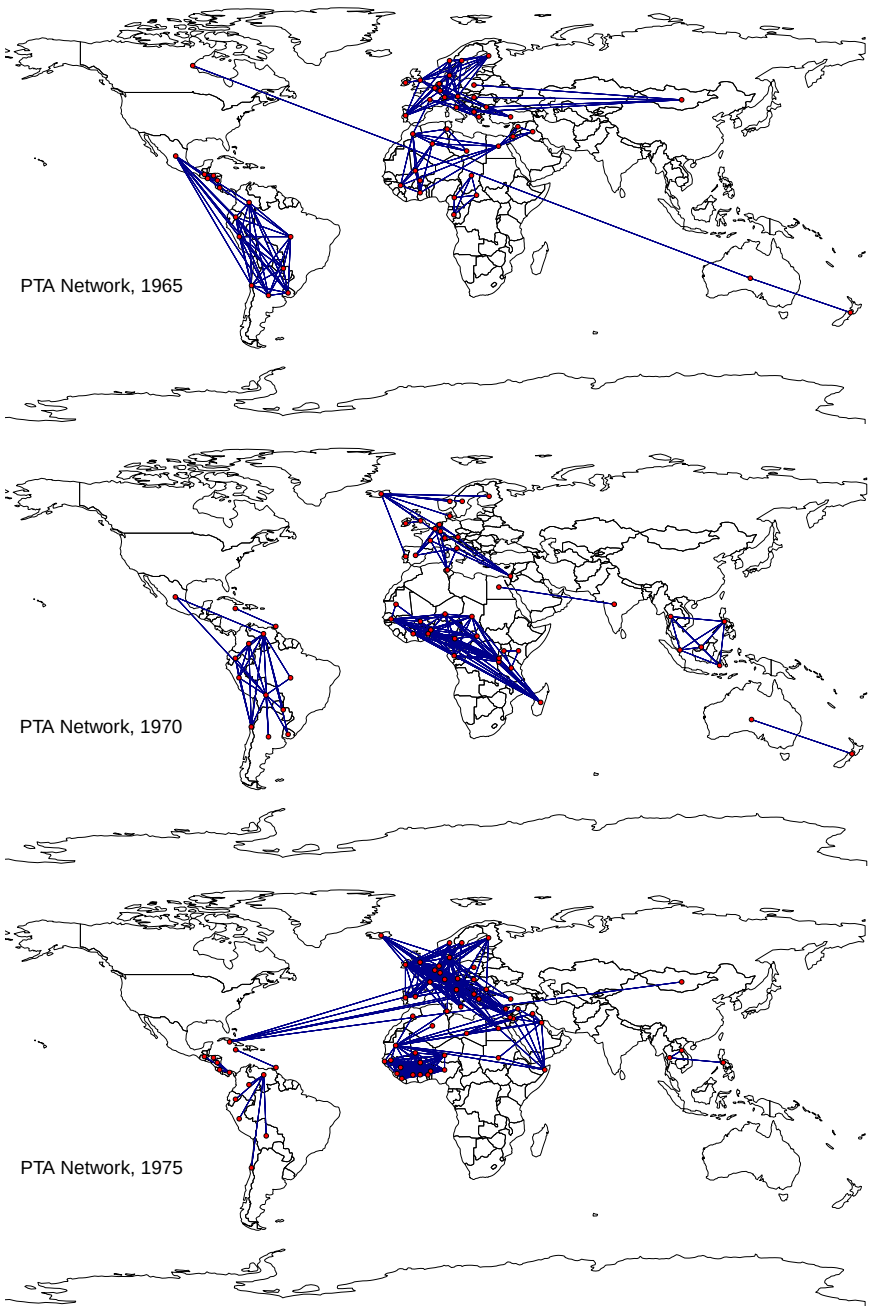


Figure 4.1 - continued

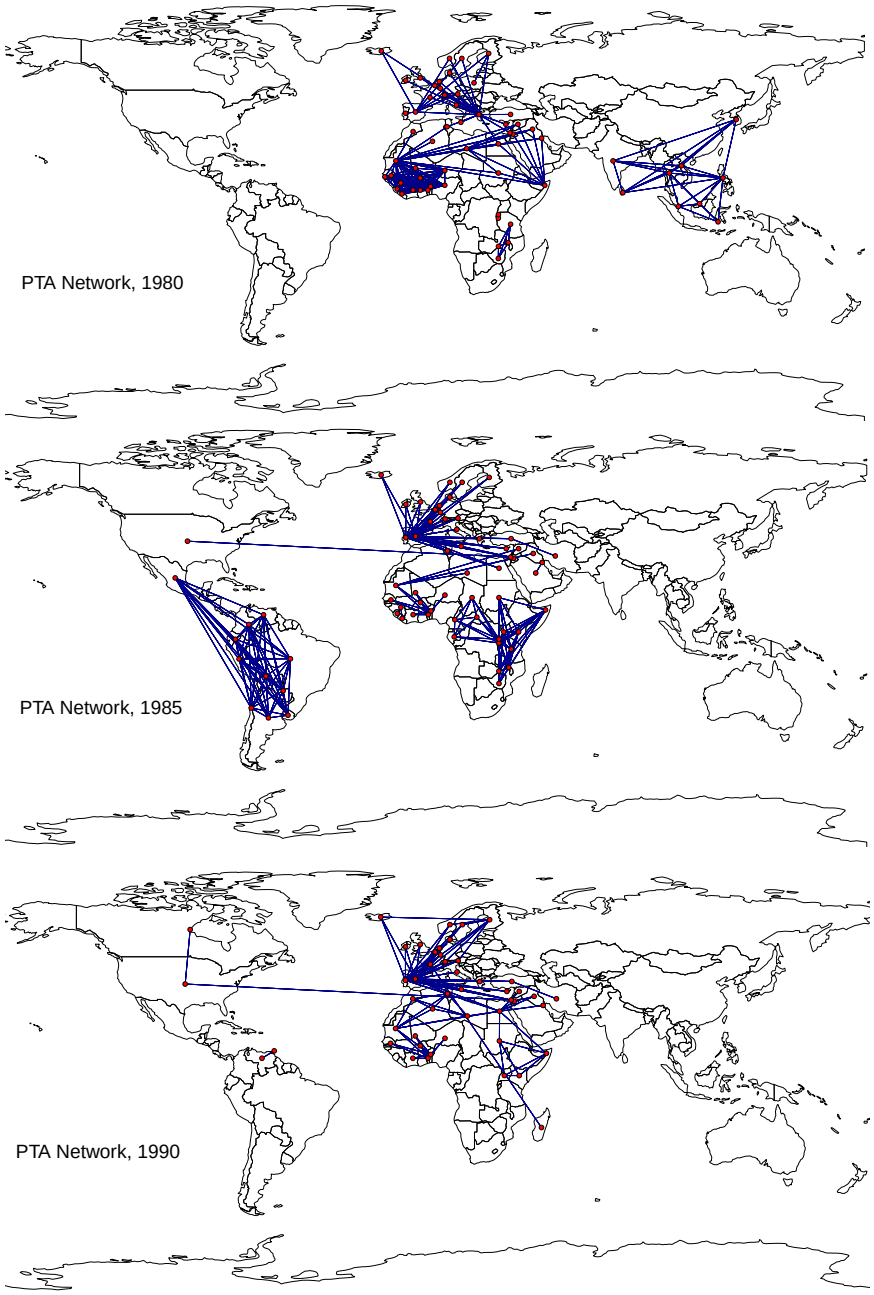
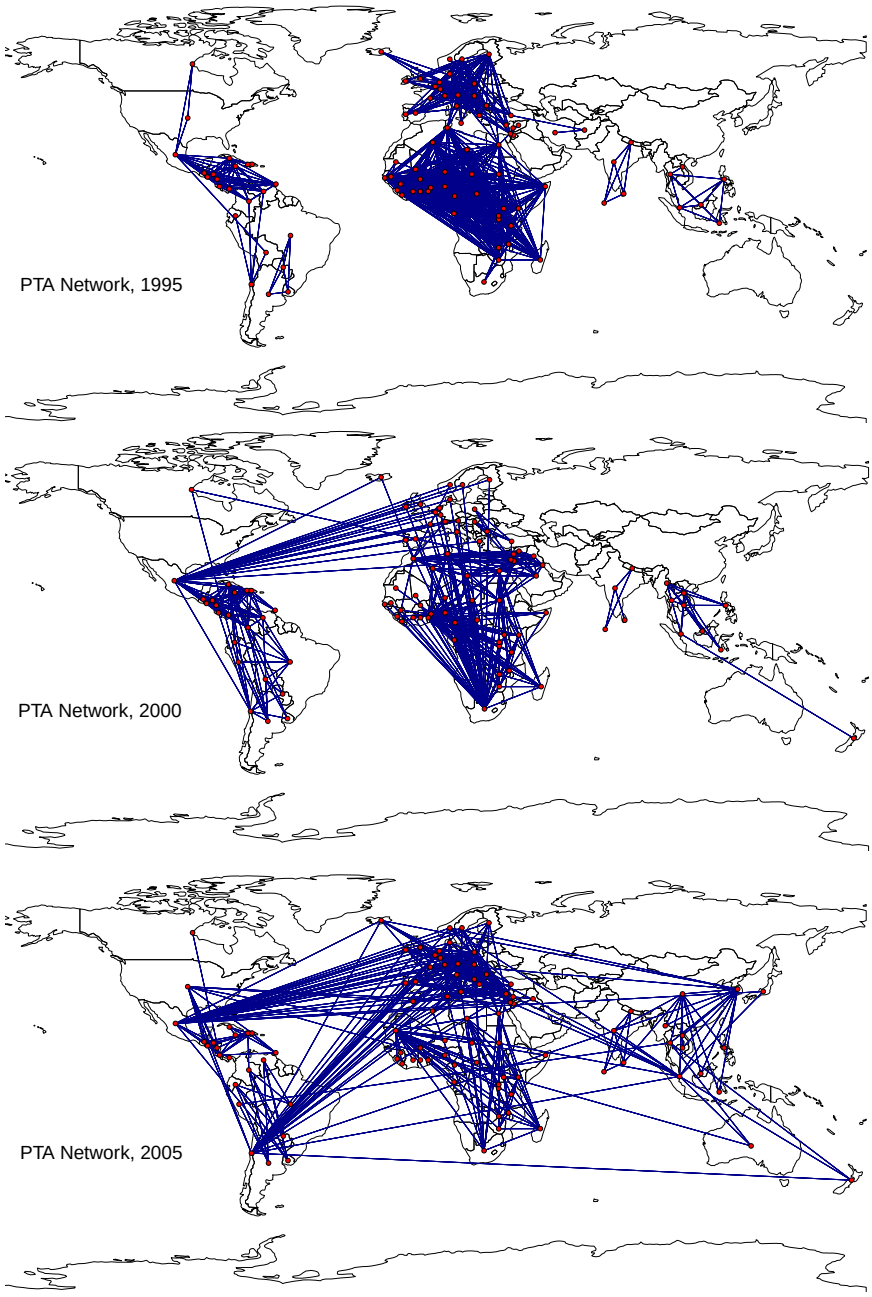


Figure 4.1 - continued



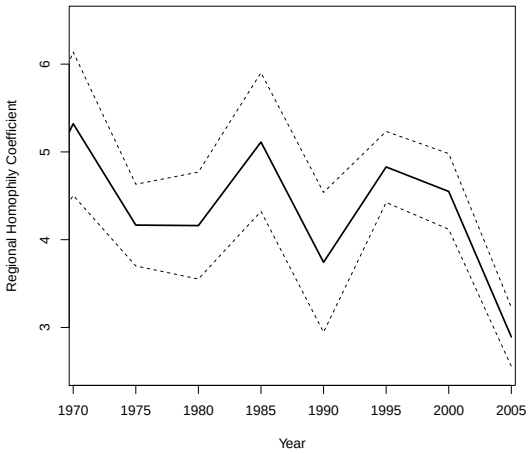
4.3 Determinants of PTA Network Formation

Applying the ERG models to the PTA networks, consider the following. Let Y represent the adjacency matrix of preferential trade agreements between all pairs of countries in the global system in each period. Each PTA network has edge and node characteristics that describe the bilateral relations between countries and country attributes respectively, denoted by X. ERGM parameters η are interpreted as the effect of a network statistic, a country (node) characteristic, or bilateral (edge) characteristic on the PTA network.

I begin by fitting a simple ERGM to the PTA network in each period to examine the determinants of treaty formation. Figure 4.2 shows the strength of regionalism over time. Estimates are based on an ERGM using homophily by geographical region and constraining the sample space to networks with the same distribution of degrees as the observed network. Countries in the same region are significantly more likely to form PTAs with one another. The propensity to form ties *within regions* dominates the propensity to form ties *across regions*. This suggests that PTAs are largely formalizing or consolidating regional trade relations, although the tendency toward regionalism has declined somewhat in recent years.

Next, I consider the economic factors that explain PTA formation. Tables 4.1 and 4.2 shows that prior trade flows strongly predict treaty formation. In both specifications, pairs of countries with more bilateral trade (at time t) are significantly more likely to form new PTAs with one another in the ensuing five-years (time t to $t+5$). The correlation is steady over time. These estimates account for bilateral trade between all country-pairs in the network. I also tested one-, two-, and three-year lags

Figure 4.2 – Regional Homophily in PTA Network Over Time



Note: Countries are categorized into 8 geographical regions. Estimates with 95% confidence intervals are from fitting a simple ERGM to PTA network. The sample space of possible networks is constrained to the actual degree distribution in the network.

and the amount of lag does not appear to matter. The estimated effect of bilateral trade is steady over time.

The size of a country's economy is also a strong predictor of PTA formation. Countries with smaller economies (measured by GDP) are more likely to join PTAs with any other country. The estimated effect has varied over time but the amount of lag does not appear to matter. Again, regionalism is a significant factor. Together, these estimates paint a clearer picture of how PTAs have proliferated. Countries tend to form trade agreements with their most important trade partners in their region; smaller countries are more apt to do so than larger countries. International economics tells us that smaller countries are likely more trade dependent because they tend to have less diverse economies and hence are less self-sufficient. Yet because the trade

volumes are positively associated with PTAs, this indicates that smaller countries are disproportionately tying themselves to larger countries within their regions.[2]

[2]These results rely on PTAs formed both within-region and across-region. I repeat the analysis within regions and get inconsistent results. Most of the intra-regional ERGMs either fail to converge or have substantial uncertainty in the estimates.

Table 4.1 – ERGM of New PTA Network Formation by Year - Effect of Bilateral Trade and GDP, Controlling for Region Homophily (Constrained by Edges)

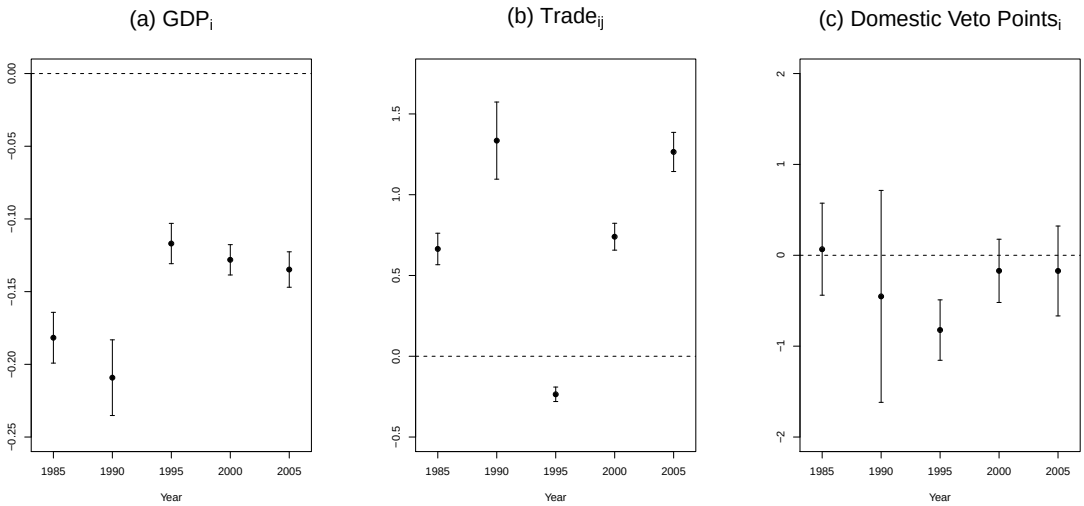
	Binary Network: Preferential Trade Agreements (by year)							
	1970	1975	1980	1985	1990	1995	2000	2005
Region Homophily	4.03***	3.08***	3.32***	3.23***	2.34***	3.21***	2.56***	1.42***
	(0.30)	(0.18)	(0.21)	(0.24)	(0.35)	(0.10)	(0.14)	(0.18)
GDP_t	−0.05	−0.11***	−0.18***	−0.08**	−0.14**	−0.20***	−0.04	−0.14***
	(0.04)	(0.03)	(0.03)	(0.04)	(0.07)	(0.02)	(0.02)	(0.04)
Bilateral Trade_t	−0.06	0.53***	0.18***	0.67***	1.43***	0.05**	0.69***	1.38***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)	(0.02)	(0.04)	(0.07)
Countries	110	110	110	110	110	110	110	110
PTA Count	136	252	175	178	90	667	356	349
Max. Degree	26	44	48	44	44	66	92	60

Note: AIC and BIC unavailable for constrained models. Significance codes *p<0.1; **p<0.05; ***p<0.01

These model specifications control for different features of the PTA network. In Table 4.1, I constrain the set of possible networks to those with the same number of edges as the observed network. This restriction ensures that only reasonable networks are used in the estimation. For instance, this specification eliminates as unrealistic a network in which no PTAs are formed or in which every country ties itself to all others. The coefficient on bilateral trade then is interpreted as estimating *which* countries join PTAs given a fixed prevalence of ties. In Table 4.2, I control for the geometric weighted edgewise shared partner distribution (GWESP). It measures the number of pairs of nodes that are connected both by a direct edge and by a two-path through another node. The significant and positive GWESP coefficient points to transitivity in the network that is beyond the transitivity that may be explained solely by nodal characteristics. This suggests countries prefer to form trade agreements with other connected countries.

Next I consider the political barriers to PTA formation. Theory predicts that countries facing substantial domestic political constraints ("veto points") hinder a country's ability to form PTAs. Table 4.3 presents the results, limited because veto points data are only available after 1980. I find little support for the theory. This suggests that even the most constrained countries with substantial divisions in political power are forming trade agreements. The one exception occurs for PTAs formed in the early 1990's. During that short period, when the number of PTAs exploded, countries that faced the most domestic obstacles appeared to be more constrained than their peers. This null result is presented in Figure 4.3(c) alongside the otherwise significant results for the economic variables, GDP (a) and Bilateral Trade (b). These estimates control for countries with contiguous territory and the GWESP distribution.

Figure 4.3 – Coefficients for PTA Network Over Time.



Note: Estimates with 95% confidence intervals are from fitting ERGM to PTA network. The model controls for whether countries are contiguous and includes a term for geometrically weighted edgewise shared partners.

Table 4.2 – ERGM of New PTA Network Formation by Year - Effect of Bilateral Trade and GDP, Controlling for Region Homophily and GWESP (Unconstrained Model)

	Binary Network:						
	Preferential Trade Agreements (by year)						
	1975	1980	1985	1990	1995	2000	2005
Region Homophily	2.10***	2.19***	1.75***	1.18***	3.04***	1.93***	1.94***
	(0.15)	(0.17)	(0.18)	(0.28)	(0.10)	(0.13)	(0.13)
GDP_t	−0.17***	−0.18***	−0.19***	−0.21***	−0.15***	−0.14***	−0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.004)	(0.004)
Bilateral Trade_t	0.56***	0.19***	0.66***	1.23***	0.02	0.67***	0.67***
	(0.04)	(0.04)	(0.05)	(0.10)	(0.02)	(0.04)	(0.04)
GWESP ($\alpha = 0$)	1.57***	1.86***	2.21***	2.85***	1.81***	1.04***	1.03***
	(0.18)	(0.21)	(0.26)	(0.37)	(0.23)	(0.14)	(0.14)
Akaike Inf. Crit.	1,224	1,010	822	301	2,755	1,702	1,703
Bayesian Inf. Crit.	1,251	1,037	849	328	2,782	1,729	1,730
Countries	110	110	110	110	110	110	110
PTA Count	252	175	178	90	667	356	349
Max. Degree	44	48	44	44	66	92	60

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01

Table 4.3 – ERGM of New PTA Network Formation by Year - Effect of Bilateral Trade, GDP, and Domestic Veto points, Controlling for Contiguous Territory and GWESP (Unconstrained Model)

	Binary Network:				
	Preferential Trade Agreements (by year)				
	1985	1990	1995	2000	2005
Domestic Veto Points$_t$	0.07	−0.50	−0.84***	−0.18	−0.15
	(0.25)	(0.59)	(0.18)	(0.18)	(0.26)
GDP$_t$	−0.18***	−0.21***	−0.12***	−0.13***	−0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bilateral Trade$_t$	0.66***	1.31***	−0.24***	0.74***	1.26***
	(0.05)	(0.13)	(0.02)	(0.04)	(0.06)
Contiguous Territory	25.07	26.15	19.43	25.80	15.86
GWESP ($\alpha = 0$)	2.71***	3.09***	1.81***	1.35***	1.25***
	(0.27)	(0.39)	(0.21)	(0.14)	(0.15)
Akaike Inf. Crit.	852	229	3,253	1,7791	1,171
Bayesian Inf. Crit.	886	263	3,286	1,813	1,205
Countries	110	110	110	110	110
PTA Count	178	90	667	356	349
Max. Degree	44	44	66	92	60

Note: Because the vast majority of PTAs are formed between contiguous countries, there is insufficient variation to estimate coefficients and standard countries, errors. Significance codes *p<0.1; **p<0.05; ***p<0.01.

4.4 Evolution of the PTA Network

The preceding analysis focused on the formation of PTAs at various "slices" of time. How has the PTA network evolved? I model the evolution of the network with a separable temporal exponential random graph models. Rather than taking the network as static at each period, the STERGM framework allows one to explicitly model the formation and dissolution of treaty ties in the PTA network. The data used in this section indicate PTAs in effect at each time period. Whereas the previous section considered only new PTA formation, this section accounts for PTAs that were formed in previous periods and persist into the next period.

Between 1970 and 2005, many new treaties were created and a very small number were dissolved. In each five-year interval, I model formations and dissolutions a separable temporal ERGMs, i.e. the transition from the 1970 PTA network to the 1975 network; the transition from 1975 to 1980; etc. The goal is to identify common factors that explain transitions over time. Results are presented in Table 4.4.

Because countries rarely exit PTAs, the PTA network becomes substantially more complex over time. Table 4.4 reflects this clearly. Between 1970 and 1995, the number edges in the network is negatively associated with the formation of new ties. This suggests a modest pace of PTA formation as countries were selective about which ties they would form. This tendency switches after 1995. During these years, the number of edges is positively associated with the formation of new ties with PTAs begetting more PTAs. Once countries form PTAs, they are reluctant to dissolve them. Edges are positively associated with the preservation of ties into the next period. Over the entire timespan, only a small portion of the PTA proliferation is driven by new

entrants. Rather, there is an explosion in the number of PTAs shared by countries already involved in one or more existing treaties.

Consistent with the previous section, the temporal analysis shows that countries with smaller economies are consistently more likely to form PTAs. Countries continue to display a strong preference for regional partners. The trade patterns, however, are inconsistent. In most but not all periods, bilateral trade is positively associated with forming PTAs. This may reflect the fact that trade is fairly stable over time and so small perturbations can influence the estimated coefficient in the formation model. The significant positive coefficient on the geometrically edgewise shared partners term reinforces the story of PTA proliferation. The higher the proportion of dyads that are tied and have neighbors in common, the more likely we are to observe new ties.[3]

Table 4.4 also displays some evidence that PTA design matters. When countries are tied with a PTA that has a dispute settlement mechanism, they are far more likely to preserve the tie. Conversely, when they lack a dispute settlement mechanism, the countries are less likely to preserve the tie, as demonstrated by the negative coefficient on the *No DSM* edge covariate. Insofar as preservation over time is an important marker, dispute settlement mechanisms are correlated with more stable PTAs. Note that because ties are so rarely dissolved, the GWESP term could not be estimated in several instances.

[3]The weight parameter is fixed at zero to simplify interpretation. By allowing the parameter to vary, we can achieve more complicated curved exponential family models.

Table 4.4 – Separable Temporal ERGM of PTA Formation and Preservation Over Time (five-year intervals) Effect of Bilateral Trade and GDP, Controlling for Region Homophily and GWESP

	Preferential Trade Agreements (by year)						
	Network Formation:						
	1970–75	1975–80	1980–85	1985–90	1990–95	1995–2000	2000–05
Edges	−3.602	−4.599*	−18.632	−5.000	−1.808*	3.971*	4.051*
	(3.678)	(1.891)	(664)	(4.29)	(1.095)	(1.640)	(2.175)
Region Homophily	2.847***	1.969***	20.312	1.168*	2.155***	4.361***	3.513***
	(0.573)	(0.231)	(664)	(0.607)	(0.162)	(0.216)	(0.329)
GDP_t	−0.108	−0.087	−0.116*	−0.078	-0.122***	−0.328***	−0.322***
	(0.110)	(0.054)	(0.054)	(0.126)	(0.031)	(0.047)	(0.063)
Bilateral Trade_t	2.318***	-0.406***	0.094	1.822***	-0.496***	0.244***	1.422***
	(0.250)	(0.068)	(0.089)	(0.271)	(0.031)	(0.052)	(0.108)
GWESP ($\alpha = 0$)		3.197***		2.079***	2.341***	2.671***	2.129***
		(0.532)		(0.458)	(0.342)	(0.574)	(0.479)
	Network Preservation:						
	1970–75	1975–80	1980–85	1985–90	1990–95	1995–2000	2000–05
Edges	2.546***	3.617**	28.293	4.972***	3.301***	29.222	5.689***
	(0.367)	(1.350)		(0.999)	(0.814)		(0.578)
No DSM_t	−1.410***	−2.368***	−0.915	−3.153***	−1.277***	-2.381	14.479
	(0.415)	(0.653)		(0.632)	(0.375)		
GWESP ($\alpha = 0$)		0.515	28.293	-0.244	-0.378		
		(1.218)		(0.831)	(0.781)		
Edge Count_t	254	294	376	443	446	745	921
Edge Count_{t+5}	294	376	443	446	745	921	1030
Cty $\geq$ 1 Edge	82	85	93	99	99	106	109

Note: Some models could not be fit with GWESP term or displayed degeneracy. Significance codes *p<0.1; **p<0.05; ***p<0.01

4.5 Impact of PTA Network on Trade Cooperation

What is the impact of preferential trade agreements on international cooperation, accounting for network structure and indirect effects? Consistent with widespread claims of politicians, this analysis finds a positive link between PTAs and subsequent trade. Countries that form PTAs are more likely to experience increases in bilateral trade with members. Table 4.5 shows results for valued ERGMs where an edge in the network denotes the volume of bilateral trade between the pair of countries. Across all periods, forming a PTA in the previous five years ($t-4$ to t) is associated with more bilateral trade (t), controlling for initial bilateral trade ($t-4$). By including initial trade as an edge attribute, I account for the trade between PTA members as well as with non-members.

Table 4.6 presents a modified valued ERGM specification where an edge in the network denotes the five-year change in bilateral trade. Because trade is measured in logged units, the outcome is percentage change. Countries that form a PTA have a greater increase in bilateral trade with one another than with other trade partners. The association is not significant in all periods. Geographical proximity and each country's GDP are not good predictors of changes in bilateral trade. In other specifications, not shown, I find dispute settlement mechanisms are not associated with subsequent changes in trade. This design element, although associated with more stable PTAs, does not appear to confer any trade benefits.

While countries frequently justify PTAs as trade-promoting measures, skeptics argue the treaties are merely "pieces of paper." These results buttress PTA advocates' claims. However, there are multiple explanations for the association between PTAs and growth in trade. First, PTAs may simply increase bilateral trade between mem-

Table 4.5 – Valued ERGM of Trade Network by Year - Effect of New PTAs and GDP, Controlling for Contiguous Territory and Initial Bilateral Trade

	Valued Network:							
	Bilateral Trade (by year)							
	1970	1975	1980	1985	1990	1995	2000	2005
Sum	−0.01	−0.24	0.03	−0.04	−0.23	−0.62	−1.36**	−0.32
	(0.45)	(0.71)	(0.60)	(0.63)	(0.42)	(0.64)	(0.57)	(0.37)
New $\text{PTAs}_{t-4 \text{ to } t}$	0.45***	0.96*	0.12	0.68***	1.80***	0.29**	0.71***	1.01***
	(0.14)	(0.50)	(0.16)	(0.23)	(0.51)	(0.12)	(0.14)	(0.31)
Bilateral Trade_{t-4}	0.72***	0.73***	0.84***	0.77***	0.80***	0.49***	0.65***	0.70***
	(0.05)	(0.07)	(0.04)	(0.06)	(0.11)	(0.02)	(0.05)	(0.03)
Contiguous Territory	1.41***	0.12	0.12	−0.15	0.73	0.46*	−0.02	−0.31
	(0.17)	(0.64)	(0.44)	(0.45)	(0.80)	(0.25)	(0.38)	(0.52)
GDP_{t-4}	−0.0004	0.01	−0.001	0.002	0.01	0.02	0.04**	0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Countries	110	110	110	110	110	110	110	110
PTA Count	136	252	175	178	90	667	356	349
Max. Degree	26	44	48	44	44	66	92	60

Note: Trade and GDP values are logged units. Reference distribution is standard normal.
Significance *p<0.1; **p<0.05; ***p<0.01

Table 4.6 – Valued ERGM of *Changes* in Trade by Year - Effect of New PTAs and GDP, Controlling for Contiguous Territory

	Valued Network:							
	Change in Bilateral Trade (by year)							
	1970	1975	1980	1985	1990	1995	2000	2005
Sum	0.53	0.17	0.25	0.06	0.19	−0.44	−0.17	−0.20
	(0.80)	(0.39)	(0.46)	(0.61)	(0.48)	(0.53)	(0.72)	(0.60)
New $\text{PTAs}_{t-4 \text{ to } t}$	1.11***	0.77***	0.22	0.14	1.51***	0.77***	0.28	0.46**
	(0.12)	(0.12)	(0.19)	(0.21)	(0.35)	(0.03)	(0.28)	(0.21)
Contiguous Territory	−0.23	−0.58**	−0.01	0.14	−0.60	−0.27	−0.55	−0.19
	(0.48)	(0.27)	(0.30)	(0.39)	(1.04)	(0.22)	(0.47)	(0.23)
GDP_{t-4}	−0.02	−0.005	−0.01	−0.002	−0.01	0.01	0.004	0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Countries	110	110	110	110	110	110	110	110
PTA Count	136	252	175	178	90	667	356	349
Max. Degree	26	44	48	44	44	66	92	60

Note: Change in trade and GDP values are logged units. Reference distribution is standard normal. Significance *p<0.1; **p<0.05; ***p<0.01

ber countries without negative repercussions for other countries. Second, they may have only a small trade-promoting effect but divert trade away from non-members. Third, they may be formed when countries anticipate—or are in the midst of—trade expansion. PTAs are a symptom of an changing trade relations. The process in inherently endogenous. To gain a better handle on these possibilities, I turn to another set of network models.

Exponential random network models jointly estimate tie formation as a function of nodal attributes and network influence on nodal attributes. I model the PTA network as a function of country characteristics and the influence of the network on country characteristics. Table 4.7 presents ERNMs that estimate the relationship between the PTA network and countries' trade dependence, a strongly endogenous process. All models control for the total edges, regional homophily, and degree dispersion. Until 1990 the association between trade dependence and PTA formation is weak. After 1990, a negative relationship between the PTA network and trade dependence emerges. The more reliant a country is on international commerce, the less likely it is to form PTAs.[4] The trend over time suggests countries have become less selective in forming PTAs and even countries that are less reliant on trade participate.

Table 4.8 presents an alternative model specification which accounts for high versus low income countries. Low-income countries are more likely to form PTAs than their high-income counterparts. When they do, they are particularly apt to form PTAs with other low GDP countries. This can be seen with the significant negative coefficient on the high GDP variable and the positive coefficient on the GDP-match covariate. Table 4.8 demonstrates that highly trade dependent countries are less likely to sign PTAs. Trade agreements do not appear to promote greater trade dependence.

[4]Selection and/or influence could be driving this association.

Table 4.7 – ERNM of New PTA Network Formation by Year as Function of High Trade Dependence, Controlling for Region Homophily, Edges, and Degree Dispersion

	Binary Network:							
	Preferential Trade Agreements (by year)							
	1970	1975	1980	1985	1990	1995	2000	2005
Edges	-3.848***	-3.492***	-3.849***	-3.114***	-4.924***	-2.153***	-2.623***	-2.608***
	(0.232)	(0.115)	(0.176)	(0.198)	(0.232)	(0.068)	(0.103)	(0.101)
Region Homophily	1.814***	2.214***	1.755***	2.152***	1.567***	6.069***	4.045***	4.034***
	(0.195)	(0.214)	(0.201)	(0.216)	(0.191)	(0.310)	(0.272)	(0.291)
Degree Dispersion	76.2***	126***	109***	96.0***	77.5***	438***	170***	171***
	(7.37)	(10.3)	(9.18)	(8.23)	(7.36)	(24.8)	(12.8)	(12.9)
High Trade Dep.$_t$	-0.172**	0.009	-0.049	-0.345	-0.028	-0.045**	-0.149***	-0.150***
	(0.078)	(0.027)	(0.050)	(0.080)	(0.055)	(0.017)	(0.037)	(0.036)
Countries	110	110	110	110	110	110	110	110
PTA Count	136	252	175	178	90	667	356	349
Max. Degree	26	44	48	44	44	66	92	60

Note: AIC and BIC unavailable for ERNM models. High trade dependence indicates above average.
Significance codes *p<0.1; **p<0.05; ***p<0.01

Table 4.8 – ERNM of New PTA Network Formation by Year as Function of High Trade Dependence and High GDP, Controlling for Region Homophily and Edges

	Binary Network:							
	Preferential Trade Agreements (by year)							
	1970	1975	1980	1985	1990	1995	2000	2005
Edges	-2.359***	-4.608***	-2.607***	-3.709***	-6.625***	-0.961***	-1.987***	-2.037***
	(0.436)	(0.311)	(0.389)	(0.360)	(0.594)	(0.200)	(0.260)	(0.252)
Region Homophily	1.616***	1.965***	1.530***	1.729***	1.270***	5.174***	3.717 ***	3.620***
	(0.189)	(0.201)	(0.188)	(0.194)	(0.180)	(0.255)	(0.252)	(0.245)
High GDP_t	-0.450***	0.253**	-0.481***	0.068	0.699***	-0.552***	-0.123	-0.107
	(0.128)	(0.083)	(0.110)	(0.092)	(0.156)	(0.061)	(0.080)	(0.078)
GDP_t Match	0.570***	1.037***	0.983***	1.305***	0.613*	1.026***	0.071	0.069
	(0.196)	(0.153)	(0.201)	(0.199)	(0.260)	(0.108)	(0.121)	(0.117)
High Trade $Dep._t$	-0.225***	0.022	-0.095	-0.364***	-0.085	-0.055***	-0.163***	-0.165***
	(0.072)	(0.040)	(0.058)	(0.071)	(0.095)	(0.016)	(0.034)	(0.035)
Countries	110	110	110	110	110	110	110	110
PTA Count	136	252	175	178	90	667	356	349
Max. Degree	26	44	48	44	44	66	92	60

Note: AIC and BIC unavailable for ERNM models. High trade dependence and GDP indicate above average. Significance codes *p<0.1; **p<0.05; ***p<0.01

CHAPTER 5

Conclusion

As countries have formed preferential trade agreements, they have created a complicated and overlapping network of treaties. This *ad hoc* network has emerged alongside the multilateral trade regime, governed by the World Trade Organization. Scholars have struggled to explain why PTAs continue to proliferate and what their collective impact is on international trade cooperation. Most agree that PTAs generate negative externalities that help explain why countries join PTAs and how these treaties impact multilateral cooperation. Yet few empirical studies account for these externalities.

By modeling PTA formation and impacts with social network analysis, this study accounts for externalities and offers more accurate estimates. Exponential random graph models capture the impact of local selection forces (e.g. node and edge characteristics) on the global structure of the network. Temporal variants lend insight into the factors that drive formation and dissolution of PTAs. And the novel class of exponential random network models further capture the impact of the network structure on the characteristics of the nodes. This is the first study to leverage these modeling techniques in the field of international political economy.

The results suggest PTAs are largely symptomatic of existing economic and political conditions. Countries with smaller economies are more likely to join trade agreements. Pairs of countries that trade more with each other are more likely to form

shared PTAs. Only in the early 1990s were countries that face significant domestic political constraints—more veto players—less likely to join PTAs. During other periods veto players are not consistently associated with treaty formation. There are strong regional trends. The majority of agreements formed in the 1970's and 1980's were between countries in the same geographical region. Recent decades have brought a growth in intra-regional PTAs, often linking countries with many existing agreements. Two general patterns characterize the growth of the PTA network. The early years were dominated by the establishment of new multi-country PTAs while later decades brought piecemeal expansion as other countries joined existing PTAs.

This analysis lends support to common claims that the PTA network is transforming international trade cooperation. The results suggest that PTAs are associated with subsequent growth in trade among member countries. At the same time, PTAs do not lead to increasing trade dependence. Because trade between countries increases after they join a PTA and trade dependence remains steady, one can infer that PTAs have sizeable negative externalities. The gains they might confer in terms of trade between members is largely at the expense of trade with non-members. Rather than expanding international economic integration, these trade agreements appear to redirect trade flows in clearly preferential ways. This reinforces the concern that PTAs are undermining multilateral cooperation, as embodied by the World Trade Organization. Yet these findings are correlative. Countries may sign PTAs in anticipation of expanding trade relations; the PTAs themselves may have no causal effect. Further research is needed to establish a causal link. Rather than precipitating dramatic economic growth—as politicians declare—the PTA network may function largely as an institutional means to lock-in economic relations. In this sense, PTAs ensure existing bilateral trade flows will remain in place and safeguard against an uncertain future.

APPENDIX A

Sample

Table A.1 – Countries Included in the Analysis

Code	Country Name	Code	Country Name
2	United States	439	Burkina Faso
20	Canada	450	Liberia
40	Cuba	451	Sierra Leone
41	Haiti	452	Ghana
42	Dominican Republic	461	Togo
51	Jamaica	471	Cameroon
52	Trinidad And Tobago	475	Nigeria
70	Mexico	481	Gabon
90	Guatemala	482	Central African Republic
91	Honduras	483	Chad
92	El Salvador	500	Uganda
93	Nicaragua	501	Kenya
94	Costa Rica	510	Tanzania
95	Panama	516	Burundi
100	Colombia	517	Rwanda
101	Venezuela	520	Somalia
130	Ecuador	551	Zambia
135	Peru	552	Zimbabwe
140	Brazil	553	Malawi
145	Bolivia	560	South Africa
150	Paraguay	580	Madagascar
155	Chile	600	Morocco
160	Argentina	615	Algeria
165	Uruguay	616	Tunisia
200	United Kingdom	620	Libya
205	Ireland	625	Sudan
210	Netherlands	630	Iran
211	Belgium	640	Turkey
212	Luxembourg	645	Iraq
220	France	651	Egypt
225	Switzerland	652	Syria
230	Spain	660	Lebanon
235	Portugal	663	Jordan
290	Poland	666	Israel
305	Austria	670	Saudi Arabia
310	Hungary	690	Kuwait
325	Italy	700	Afghanistan
338	Malta	710	China
339	Albania	712	Mongolia
350	Greece	732	South Korea
352	Cyprus	740	Japan
355	Bulgaria	750	India
375	Finland	775	Myanmar
380	Sweden	780	Sri Lanka
385	Norway	781	Maldives
390	Denmark	790	Nepal
395	Iceland	800	Thailand
420	Gambia	811	Cambodia
432	Mali	812	Laos
433	Senegal	820	Malaysia
434	Benin	830	Singapore
435	Mauritania	840	Philippines
436	Niger	850	Indonesia
437	Cote D'Ivoire	900	Australia
438	Guinea	920	New Zealand

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