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Reconstructing and Analyzing the Transnational Human Trafficking Network

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***Abstract*—Human trafficking is a global problem which impacts a countless number of individuals every year. In this project, we demonstrate how machine learning techniques and qualitative reports can be used to generate new valuable quantitative information on human trafficking. Our approach generates original data, which we release publicly, on the directed trafficking relationship between countries that can be used to reconstruct the global transnational human trafficking network. Using this new data and statistical network analysis, we identify the most influential countries in the network and analyze how different factors and network structures influence transnational trafficking. Most importantly, our methods and data can be employed by policymakers, non-governmental organizations, and researchers to help combat the problem of human trafficking.**

I. Introduction

Human trafficking, the recruitment, harboring, transportation, provision, or acquisition of individuals for coerced exploitation, is one of the most important humanitarian issues facing governments across the globe. It is estimated that over 20 million victims of human trafficking are currently exploited for forced labor or sex in both high income and low income countries [1], [2]. This exploitation is estimated to produce a combined annual profit of approximately US$150 billion for traffickers, which, if accurate, makes human trafficking one of the largest contemporary global criminal enterprises [3]. Given the scale of the human trafficking problem, it is unsurprising that the issue has gained increased attention from national governments, international organizations, non-governmental organizations, and researchers in recent decades.

We build on this work by introducing an approach that uses techniques from natural language processing and machine learning to produce data on global transnational human trafficking. We generate this network data from country profiles in the Trafficking in Persons Report (TIP), an annual publication from the United States Department of State. We process these texts, find and extract entities in the texts, and classify relationships between the entities. The output of this process is data on bilateral trafficking relationships between countries, which we make publicly available.[1]

We employ network analysis to provide evidence that the networks we construct have validity, and capture important realities about global human trafficking. Of particular relevance to policymakers, we identify which countries are most central in the trafficking network. Our analysis indicates that trafficking outflows are more likely in lower income countries; victims are more likely to be trafficked to high income countries; trade, refugee, and immigrant flows all facilitate trafficking; the trafficking network has structural redundancy and is therefore robust to localized disruptions in transport channels; and there are a number of hub-countries which play an important role in the transnational trafficking network.

This work therefore generates new insights and knowledge about human trafficking activities, while also contributing to both the social networks literature and the burgeoning computational social science literature [4]–[6]. Although the source data we use has been used by other researchers to study human trafficking [7]–[9], to our knowledge, we are the first to provide an approach for generating network data on transnational human trafficking and to study the structure of this network. More broadly, this research also illustrates the potential for using information extraction and machine learning techniques to construct quantitative representations of qualitative data without excessive costs.

In the next section, we provide background information on the history and content of the TIP. We then describe the process of generating the network data from the text of these reports. We present our analysis of the transnational global human trafficking network. We conclude by discussing the implications of our work.

II. Related Work

Work and measures by governments and international organizations to alleviate the problem of human trafficking are perhaps more developed than research on the topic [10]. This is potentially explained by the fact that human trafficking

[1]This data can be obtained from https://github.com/cib117/trafficking.

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is an illicit criminal enterprise and perpetrators endeavor to hide their actions, thereby making it difficult to obtain high quality statistics on human trafficking activities. Despite the challenges involved in identifying information on human trafficking, researchers have nevertheless conducted both micro-level and macro-level empirical analyses of human trafficking.

In micro-level studies, trafficking victims are most commonly interviewed or surveyed for information on the actors involved in the trafficking process, the transit experience of victims, the working and living conditions of victims, and the abuses suffered by victims [11]–[16]. Other approaches used in micro-level studies include using court records to study local trafficking networks and analyzing the issuance figures of particular types of visas [17], [18].

In macro-level studies, researchers typically explore how well different political and economic factors explain cross-national variation in human trafficking using data from TIP reports published in particular years and cross sectional data on human trafficking from the United Nations Office on Drugs and Crime (UNODC) [7]–[9], [19]. From this work, it appears that trafficking outflows are greater in poorer countries and countries where the economy is transitioning, whereas wealthier countries have greater trafficking inflows.

Moving away from these traditional social science research designs, researchers have also started to use internet data and machine learning techniques to identify and locate trafficking victims and domestic human trafficking networks [20]–[23]. These systems show that text of escort advertisements provide useful information for uncovering traffickers and can assist law enforcement and non-governmental organizations locate and save trafficked individuals.

III. Data

For this study, we extract data on the transnational human trafficking network using the text of country narratives contained in the TIP report. The TIP report is an annual publication that is issued by the United States Department of State. The TIP report was first published in 2001 after the United Congress approved the Victims of Trafficking and Violence Protection Act [24]. This act ordered the Department of State to produce an annual report that describes human trafficking activities in countries and evaluates national governments' responses to trafficking. To meet this requirement, the TIP report contains detailed country narratives which outline human trafficking issues and activities in a country, provide information on transnational trafficking routes, discuss governments' legislation to combat trafficking, and classifies a country into one of four tiers which scores a country's anti-trafficking efforts. A classification as a Tier 1 country is the best outcome possible for a country and suggests a country is putting significant effort into combating trafficking, whereas a classification as a Tier 3 country indicates that a country's trafficking efforts are unsatisfactory [25]. A bottom tier ranking can result in economic punishments towards the offending country and governments therefore often take action to obtain and maintain a good score [26]. There are 189 countries included in the most recent version of the TIP, and each of these countries has a report generated annually. Figure 1 is a sample of TIP text with the countries extracted highlighted.

Text: *Men and women from* ***China****,* ***the Philippines****,* ***Vietnam****,* ***Indonesia****, and other countries in Asia, the Middle East, and South America are subjected to forced labor in South Korea; some women from these regions are subjected to forced prostitution. Migrant workers, especially those from* ***Vietnam****,* ***China****, and* ***Indonesia****, can incur thousands of dollars in debt, contributing to their vulnerability to debt bondage. Approximately 500,000 low-skilled migrant workers, many employed under the government's employment permit system, work in fishing, agriculture, livestock, restaurants, and manufacturing; some of these workers face conditions indicative of forced labor. Some foreign women on E6-2 entertainment visas — mostly from* ***the Philippines****,* ***China****, and* ***Kyrgyzstan*** *— are subjected to forced prostitution in entertainment establishments near ports and U.S. military bases. Some women from* ***China****,* ***Vietnam****,* ***Thailand****,* ***the Philippines****, and* ***Cambodia*** *who are recruited for marriage to South Korean men through international marriage brokers are subjected to forced prostitution or forced labor after their arrival. The ROK is a transit point for Southeast Asian fishermen subjected to forced labor on fishing ships bound for* ***Fiji*** *and other ports in the Pacific.*

Extracted Entities: *China*, *the Philippines*, *Vietnam*, *Indonesia*, *Kyrgyzstan*, *Thailand*, *Cambodia*, *Fiji*.

Fig. 1. Sample Trafficking in Persons Report Text

As is the case with most government produced sources, there is potential for bias within this data. Particularly, it has been contended that there is evidence of a shifting standard as to what constitutes human trafficking [24]. This meant an early focus on sex trafficking, which was quickly amended to include other forms of trafficking. Additionally, a discontinuity exists between pre and post-2009 documents, where the scope of the report was expanded to include coverage of more nations. A final concern is that, as with all data on dark or illicit networks, human trafficking is an activity that is deliberately hidden by its perpetrators.

However, while an inherent degree of skepticism is needed, it is also important to remember that the TIP report has been used by numerous human trafficking researchers and is considered one of the most extensive sources of information on human trafficking [8], [9]. Moreover, we believe that in classifying general flows between countries, some of these concerns are ameliorated.

IV. Generating Network Information from Text

We transform these reports into network data with the following process: 1) obtain the reports; 2) prepare the text of reports for analysis; 3) identify entities from the text and

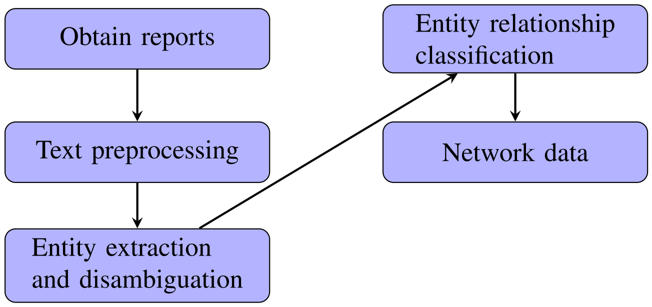

Fig. 2. Outline of framework for generating data

disambiguate these entities for each country report; and 4) classify the dyadic relationships between countries.

A. Obtaining the data

The country narratives from the annual TIP report are published online on the State Departments website.[2] To obtain this data, we wrote custom scrapers to download and extract the text of the country narratives. The format of the webpages changes considerably over time, necessitating multiple custom programs. However, in recent years, the structure has remained reasonably consistent, and we think this process will only require minor maintenance for future iterations of the report.

B. Text preprocessing

After extracting the raw text from the webpages and prior to identifying entities in the text of reports, we implemented a couple of preprocessing steps to prepare the text for analysis. We first identified and extracted the first section of each report, which summarizes the trafficking situation of a given country. We do this because this section lists all countries that victims are trafficked to and/or trafficked from. We then identified sentences that related to sex tourism in a given country and removed these sentences as they often contained relevant entities but did represent a trafficking relationship between a pair of countries. Similarly, we removed sentences discussing Native Americans as these can prove problematic in the entity extraction process and do not provide any information on transnational human trafficking. The remaining text from the first section of the reports was employed for entity extraction.

C. Entity extraction and disambiguation

The key step in the entity extraction process is to find all country names, or other nouns that refer to a country, within this text for each country report. To identify these entities, we employed an extensive gazetteer that was originally created to generate political event data from text of newswire reports [27]. For each report, we identify country names and other entities that refer to a country that are contained in both the report and the gazetteer.[3] We do not extract the entities that refer to the country being reported on as these do not provide any information about transnational trafficking. As an example, we present the text of the first section of the 2013 country report for South Korea in Figure 1, highlighting all the entities found in the text. From this report, we can identify, among other things, that trafficking victims from China, the Philippines, Vietnam, and other countries are found in South Korea.

TABLE I
NER IDENTIFICATION OF COUNTRY NAMES IN REPORTS

Model	Accuracy
spaCy	0.93
Stanford Named Entity Recognizer	0.97

We took this approach for a few reasons. Firstly, we assessed the performance two commonly used Named Entity Recognition (NER) tools, the Stanford Named Entity Recognizer and spaCy [28], [29], for identifying country names from a random sample of 175 TIP reports. We present these results in Table I. While we find that both these models boast very high accuracy for this task, they also systematically fail to identify certain countries. For example, Cote d'Ivoire is never correctly identified by the Stanford NER model. While this may not seem like a particularly important issue, this can have important consequences for downstream tasks. The failure to recognize this entity means, for instance, we would not identify a total of 25 trafficking relationships between Cote d'Ivoire and other countries in 2016 alone.

Moreover, from a detailed reading of a number of reports, there are a number of non-location entities such as "Chinese", "Syrian", and "Russian" contained in the reports that are important for understanding trafficking connections between countries and specified in the gazetteer, but do not fit neatly into the classes of popular NER tools.[4] Finally, the gazetteer also enables us to easily disambiguate entities and relate the extracted entities to a set list of standardized country names. This ensures, for instance, that the entities "China", "Chinese", and "People's Republic of China" are not represented as distinct nodes in the final network.

D. Entity relationship classification

The above process enables us to easily extract all of the sentences in particular country's report that mentions another country. This is the unlabeled data that we use to classify the nature of relationships between countries, consisting of the name of the country the report is about, a sentence where another country or countries is mentioned, and the names of those entities. The classification task here is to label whether or not each of these country pairs represents a sending relationship or a receiving relationship.[5]

[2] For example, the country narratives from the 2016 report can be found at https://www.state.gov/j/tip/rls/tiprpt/countries/2016/index.htm.

[3] After examining the gazetteer, we also added a small number of potentially relevant entities to it.

[4] These entities are classified as a miscellaneous entity along with a number of other irrelevant entities. Correctly extracting the relevant entities in this category would therefore also require a custom dictionary.

[5] To be clear, a country pair comprises of the country which the report is about and one of the other countries which are mentioned in that same report.

TABLE II
CLASSIFICATION OF COUNTRY PAIR RELATIONSHIPS

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.85	0.85	0.85	0.85
SVM	0.85	0.85	0.85	0.85
Naive Bayes	0.84	0.84	0.84	0.84
Random Forests	0.81	0.83	0.81	0.81

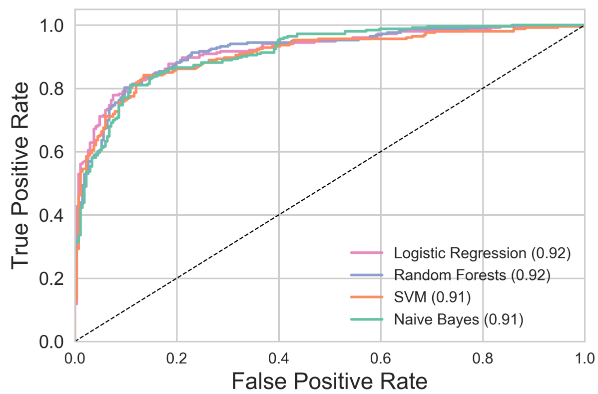

Fig. 3. ROC curves for classifiers.

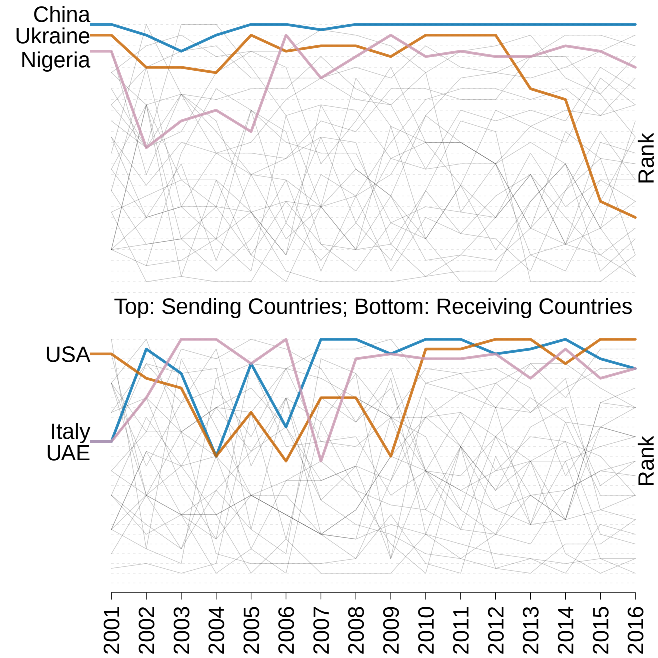

Fig. 4. Top twenty-five sending and receiving countries.

To construct a training set, we take advantage of the fact that some countries, during certain years, act as only sending or receiving points for trafficked people and are labeled as such in the reports. There are over 1500 such sentences in the corpus. We supplement this data by hand annotating over 1200 additional sentences, creating our final labeled data set.[6]

For classification, we represent each sentence in which an entity is mentioned as unigrams and bigrams, or counts of words and two word phrases that appear in each sentence. We use this data with a number of popular machine learning classifiers for text classification tasks, specifically, Multinomial Naive Bayes, Random Forests, Support Vector Machine, and regularized Logistic Regression [30]–[32]. We used 10-fold cross validation to tune the respective hyperparameters of these models and held out 20% of the labeled data as an independent test set to compare classifier performance. We estimated these models using scikit-learn, a Python library that implements numerous machine learning algorithms [33].

To compare the predictive accuracy of our models we present various accuracy in Table II, and plot a ROC curve for each classifer in Figure 3. From this, we can see that the general performance of the classifiers is quite strong. The Logistic Regression has the strongest performance with an accuracy score of 0.85, a F-1 score of 0.85, and a ROC area under the curve value of 0.92. We therefore employ the estimated parameters of this model to classify the country pair relationships for the unlabeled data.

[6]In a small proportion of sentences, both the origin and destination countries are mentioned in the same sentence. This means some of the entities in these specific cases will be necessarily misclassified using this sentence level approach.

V. CONSTRUCTING THE NETWORK

The process outlined above produces labeled annual human trafficking data in the form of a directed edgelist. Summary statistics from this data is useful for identifying temporal patterns in important sending and receiving countries. We demonstrate this in Figure 4 by plotting the annual rank of the top twenty-five trafficking countries by sender and receiver. The two sets of highlighted countries are respectively the top three senders and receivers. From the crossing lines, which indicate changes in ranking, we see that the worst violators of human trafficking tend to be stable in both groups, especially post-2009 when the TIP Reports became more consistent [24].

We next transform these edgelists into a network adjacency matrix. We begin by determining the population of relevant entities in this system. To do so, we identified the entities named in the TIP Reports, countries in the international system, and countries for which data on predictors relevant to trafficking behavior exists. As previously noted, reporting practices prior to 2009 are different from current ones. Specifically, before 2009, the TIP report was limited to eighty-three countries that were assessed as being involved in significant trafficking flows [24]. Since this criteria was removed, the number of countries included in the report have remained relatively consistent, with 175 in 2009 and 188 in 2016. We therefore consider the scope of the TIP report post-2009 to be exhaustive of countries in the international system and draw upon a standard list of countries used by researchers of international relations [34]. Countries on this list but not in the TIP report are included in the network and taken to be non-traffickers. For the purpose of modeling the network, we were forced to

TABLE III
EVIDENCE OF TRAFFICKING FROM HUNGARY TO AUSTRIA

Year	Text Evidence
2009	*Austria is a transit and destination country for women and children trafficked from ... Hungary*
2010	*Women from Hungary are forced into prostitution in ... Austria*
2011	*Women from Hungary are forced into prostitution in ... Austria*
2012	*Women from Hungary are forced into prostitution in ... Austria*
2013	*Hungarian women and children are subjected to sex trafficking within the country and in ... Austria*
2014	*Women and children ... are subjected to sex trafficking within the country and abroad ... Austria*
2015	**No evidence**
2016	*Hungarian women and children are subjected to sex trafficking within the country and abroad... Austria*

TABLE IV
HIGH RANKING COUNTRIES BY DIFFERENT TYPES OF CENTRALITY

In Degree		Out Degree		Betweenness	
USA	.025	China	.037	China	.155
China	.024	Nigeria	.022	USA	.068
Italy	.019	Ukraine	.020	Nigeria	.045
UAE	.018	India	.020	India	.032
Sweden	.016	Thailand	.020	Guinea	.032

remove a small subset of countries due to lack of coverage in relevant data. Generally, the excluded entities are small island nations, micro-states, and territories. We end up with 178 countries in our system. In the following analysis, we focus on these countries during the 2009–2016 period. As the countries included in the most recent reports are largely exhaustive of the international system, future research in this area benefits from the fact that the countries included in the TIP Reports will be relatively stable.

Next, we collapse these annual networks into a single network spanning the 2009–2016 period. Patterns in the data suggest that there are substantial variations in the trafficking network from year to year, likely due to non-recurrent global events and reporting differences, such that a yearly examination, while insightful, can also obscure underlying systematic patterns that are useful for longer term policies aimed at trafficking prevention. Consider, for example, that 177 dyads are named in seven of the maximum eight years, as is illustrated of the Hungary-Austria dyad in Table III. From this table, we can see that there is evidence of trafficking from Hungary to Austria in every year in the time period, except 2015. It is unlikely that there was no trafficking between Hungary and Austria in 2015, rather, given the illicit nature of trafficking, such activity was instead not uncovered/reported.

Based on this evidence, we therefore believe it is more reasonable to collapse the annual networks into a pooled period instead of modeling the network on a yearly basis. Specifically, a dyad is specified as a trafficking dyad as long as it is named in at least one TIP report from 2009–2016.

A. Descriptive Network Statistics

The resulting network has a total 178 country nodes and 2671 directed and unweighted edges. To provide basic information on the transnational human trafficking, we first provide a descriptive analysis of the network.

1) Centrality: Among the most important questions, both for policymakers and as a check on face validity, when analyzing the global trafficking network, is which countries are most central to the network. In this exploratory analysis, we examine commonly used measures of network centrality for directed networks: in degree, out degree, and betweenness.

Degree centrality is the most basic centrality measure, providing a score for the amount of normalized edges that a given country has. In the context of human trafficking, this means that the greater a node's degree centralization, the more established trafficking flows it has. For a directed network such as this one, degree centrality is more meaningful when it considers inflow and outflow edges separately, as tendencies for sending and receiving depend on different factors. From Table IV, we can see that the USA, China, Italy, UAE, and Sweden are prominent destinations. China is also an important source country, as are Nigeria, Ukraine, India, and Thailand.

Betweenness centrality measures how important particular nodes are for facilitating flow across the network. Betweenness centrality is calculated by finding the number of shortest paths between all node pairs that pass through a given node, normalized by the total number of node pairs. In the context of human trafficking, a node with a high betweenness centrality would indicate nodes that serve as intersections, or where large flows pass through. From Table IV, the countries with the highest betweenness centrality scores are China, USA, Nigeria, India, and Guinea. Note here that a small number of nodes are responsible for a very high number of shortest paths (i.e. the distribution of betweenness centrality is very skewed). This provides initial evidence that the human trafficking network contains important trafficking hubs.

2) Reciprocity: Reciprocity is the extent to which the existence of directed edges between a pair of nodes is contingent on the existence of an edge on the same node pair from the opposite direction. This is shown in Figure 5 with bidirectional flow between China and Thailand. The human trafficking network is characterized by a moderate level of reciprocity, as measured by the correlation between edge values on node pairs $\rho = 0.39$ [35]. This suggests that trafficking flows within a pair of countries is governed by more than push and pull factors at the country level. Instead, dyadic factors, possibly the existence of established transportation infrastructure, also influence trafficking.

3) Transitivity: The network is also characterized by evidence of transitive structures, with a global weak transitivity of 0.30. This means that in 30% of two paths, the head of the path also directly sends an edge to the tail. This is shown in Figure 5, with North Korea as the head and South Korea as the tail. The presence of these structures indicate the potential for robustness (i.e. redundancy) in trafficking channels; in the example shown, trafficking victims can be transported from North Korea to South Korea either directly or indirectly via

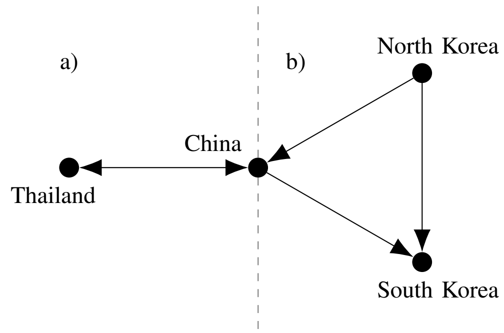

Fig. 5. Examples of a) reciprocity and b) transitivity in the trafficking network.

China; hence, even if direct trafficking channels are disrupted, flow between source and destination can be maintained.

VI. Modeling the Transnational Human Trafficking Network

Our reconstructed network enables substantive investigations into human trafficking patterns in the global system. We consider this system to be a relational one, in which there are network effects such as reciprocity and transitivity that drive formation between nodes [36]. The descriptive network statistics discussed previously provide initial evidence that network effects are present in the trafficking network, but because these effects can have similar observable implications, it is difficult to identify which effects contributed to the observed network. To overcome this difficulty, we turn to inferential network statistics, specifically the exponential random graph model (ERGM) that allows us to examine different network effects conditional on all other modeled effects [37].

A. Exponential Random Graph Model

An ERGM is a statistical model that allows for inference on factors that contribute to the formation of an observed network, including monadic, dyadic, and network effects. Results from a fitted ERGM, similar to those from a standard regression model, are estimates that represent the effect of the specified factors on the observed outcome. Using this approach, we can determine whether hypothesized behavioral tendencies beyond country characteristics systematically contribute to the relational patterns within a system.

The intuition of the ERGM approach is that the observed system, that is the entirety of ties between nodes on the network, is treated as a single realization of a multivariate distribution $\boldsymbol{Y} = \{Y_{ij}\}$ where Y_{ij} is the tie variable between nodes i and j [38], [39]. Because the entire network is jointly modeled as a single observation, the assumption required in standard regression models for conditional independence between dyads is relaxed. Factors hypothesized to be a part of the network generating process, represented by local network configurations or by nodal or dyadic attributes, are specified as a set of network statistics and the effect of each statistic on the probability of observing the realized network, conditional upon the existence of all other specified statistics, can then be estimated. Specifically, the probability of observing the network $\boldsymbol{Y}$ is given by Equation 1:

$$Pr(\boldsymbol{Y}, \boldsymbol{\theta}) = \frac{1}{\kappa} \exp\{\boldsymbol{\theta}' \boldsymbol{h}(\boldsymbol{Y})\} \quad (1)$$

where $\boldsymbol{\theta}$ is a vector of parameters and $\boldsymbol{h}()$ is a vector function such that $\boldsymbol{h}(\boldsymbol{Y})$ yields a vector of observed network statistics computed on $\boldsymbol{Y}$. κ is the normalizing constant that makes the equation a probability density function.

Network effects are included in the ERGM by specifying network terms that capture the underlying generative model for the observed network. The vector function $\boldsymbol{h}()$ is highly flexible in what is a permissible specification, limited only by the criterion that $\boldsymbol{h}$ is finite when evaluated over a binary network [37], [40]. This is important because global systems such as the human trafficking network rarely comprise of only independent bilateral relations [36].

TABLE V
ERGM Network Terms

	Network effects represented by local network configurations
1	A count of **edges** captures the baseline probability for tie formation.
2	A count of **reciprocated edges** captures the tendency for directed ties to be returned.
3	The **geometrically-weighted in-degree** distribution is a statistic that captures asymmetry in the tendency for actors to receive ties.
4	The **geometrically-weighted out-degree** distribution is a statistic that captures asymmetry in the tendency for actors to send ties.
5	The **geometrically-weighted dyadwise shared partner** distribution is a statistic that captures redundancy or structural equivalence in the network.
6	The **geometrically-weighted edgewise shared partner** distribution is a statistic that captures transitivity in the network.

B. Model Specification

Patterns of human trafficking are governed by 1) demand and supply factors at the country level and by 2) infrastructure and logistics surrounding illicit human transportation. From a broad review of existing studies on patterns of human trafficking, [9] identifies four country level factors that influence the supply and demand of human trafficking: migration, the existence of vulnerable populations, crime, and institutional efforts at decreasing trafficking. Given our network data, we are able to explore factors that extend beyond country-level characteristics. Specifically, we also examine factors at the dyad-level relating to established infrastructure, and network effects based on the exploratory descriptive network analysis above: hub-like structures that govern flow, reciprocal flow, and the presence of redundancy in trafficking channels. To capture these network effects, we include the network statistics summarized in Table V. The data used for country and dyad measures are obtained from international organizations (e.g. United Nations) and academic sources. These measures and their data sources are summarized in Table VI.

C. Results

We present the coefficient estimates and standard errors from our ERGM model in Table VII. The model contains

TABLE VI
MEASURES AND DATA SOURCES

Measure and Data	Time Period
Monadic Variables	
Median Per Capita GDP (UN)	2009–2016
Law Prohibiting Child Marriage (WDI)	2015
Median Workforce Gender Ratio (WDI)	2009–2016
Median Rule of Law Quality (WGI)	2009–2016
Median Human Rights Score [41]	2009–2013
3rd quartile Conflict Deaths (UCDP)	2009–2016
Dyadic Variables	
Median Imports/Exports (COW)	2009–2014
Total Immigration [42]	2005–2010
3rd quartile refugees/asylum-seekers (UN)	2009–2016
Geographic Contiguity (COW)	In 2016

three sets of coefficients: country-level factors that govern supply and demand, dyad-level factors relating to logistics and infrastructure, and network effects. The findings for country-level factors corroborate prior studies [9], which supports the validity of our network. For example, high income countries are likely receivers while low income countries are likely senders. Another set of country-level factors are the existence of legal and governance institutions, captured by the World Governance Indicators and Human Rights Scores [41], that should in theory reduce trafficking. Our results indicate that these institutions are a more effective deterrent in the sender country compared to in the receiving country.

At the dyad-level, results indicate that all types of flow, including trade, immigrants, refugees, and asylum seekers, creates infrastructure that enables trafficking flows. Along the same lines, it is understandable that two countries with shared borders, by land and by sea, are likely to be trafficking pairs.

Finally, we discuss network effects, which previous studies that do not model trafficking patterns as a network cannot detect. Based on the combination of estimated parameters on our included network terms, we have a number of findings that support our expectations. First, it appears that hub-formation is a strong underlying generative feature of the human trafficking network. This is supported by a combination of positive geometrically-weighted in- and out-degree terms, which capture the tendency for asymmetries between countries in receiving and sending, suggesting the presence of a small number of hub-countries.

Second, reciprocal tie formation is a feature of the human trafficking network, with country pairs more likely to have bidirectional than unidirectional flow. Note that this tendency is conditional on dyad-level factors relating to logistics and infrastructure. There are two plausible explanations for this finding. It might be the case that established infrastructure beyond those included in our model plays an important role in facilitating trafficking, or that there is some type of unmodelled homophily in the demand for trafficking.

Third, the network exhibits tendencies for redundancy in flow paths, indicated by the positive coefficient on the geometrically weighted edgewise shared partner term. This means that

TABLE VII
ERGM OF HUMAN TRAFFICKING NETWORK 2009–2016

Effects	Est.	s.e.
Network Effects		
Edges	-3.39	0.33
Reciprocity	1.90	0.09
GW In-Degree	4.59	0.93
GW Out-Degree	0.94	0.32
GW Dyadwise Shared Partner	-0.05	< 0.01
GW Edgewise Shared Partner	1.37	0.07
Country-level Factors		
Receiver Human Rights Score	0.06	0.03
Sender Human Rights Score	-0.20	0.03
Receiver GDP Per Capita	0.08	0.03
Sender GDP Per Capita	-0.22	0.03
Receiver In Conflict	0.15	0.05
Sender In Conflict	-0.38	0.05
Receiver Workforce Gender Ratio	-0.48	0.12
Sender Workforce Gender Ratio	0.97	0.11
Receiver Anti-Child Marriage Law	-0.29	0.05
Sender Anti-Child Marriage Law	0.09	0.06
Receiver Rule of Law	-0.05	0.05
Sender Rule of Law	-0.15	0.05
Dyad-level Factors		
Dyadic Immigration	0.04	< 0.01
Dyadic Refugees/Asylum Seekers	0.04	< 0.01
Dyadic Trade	0.10	0.01
Contiguity by Land	1.47	0.09
Contiguity by Sea	0.67	0.10

Log likelihood = -5678.179; AIC = 11402; BIC = 11595
Estimation conducted using the `ergm` package in `R`.

the type of multiple pathing between source and destination, such as the North Korea-South Korea-China triad illustrated in Figure 5, are likely to be formed. These type of redundant structures introduce robustness into the network, as disruptions of transportation channels between two countries will lead to diversion of trafficking flows instead of stopping them.

VII. CONCLUSION

A fundamental problem in studying global human trafficking is the lack of available consistent data on the issue. In this project we present an original low cost process involving text data and machine learning that generates network data on transnational human trafficking. In our analysis of this data, we identified network effects that govern trafficking patterns in the network. Most important are our findings about the tendency for hub-formation and for redundancy in trafficking paths. The combination of these two factors leads to the policy recommendation that interventions should target important hub countries instead of specific trafficking paths between countries, as disruptions to specific paths will simply lead to diverted flows.

Additionally, our study demonstrates the potential of this data for gleaning new insights into transnational human trafficking activities. We believe that building on our approach and exploring the utilization of recently developed methodologies for generating human trafficking data is a promising topic for future research [43], [44]. We hope that by making our approach and data publicly available, policymakers and researchers with developed, substantive knowledge of human trafficking can utilize it to combat global human trafficking.

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