Designing Policies to Prevent Sex Trafficking: A Cellular Automata Approach

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Abstract

This paper applies spatial analysis tools to study sex-trafficking flows in countries around the world. My analysis shows that while countries differ greatly, the countries that share spatial and geographical characteristics tend to also share the factors affecting the intensity of sex trafficking. This finding suggests that while there is no single cure-all anti-trafficking policy, optimal policies can be designed for each group. This conclusion is in sharp contrast with how anti-trafficking policies are currently designed: Each country is given recommendations to comply with one general policy model.

1. Introduction

Sex trafficking has been long recognized as a form of violence against women and it has been a frequently studied subject in multiple fields of social science, particularly in psychology, sociology and women's studies (Brown, 2000; Farley, 2007; and Kara, 2009). The main focus of these studies has been on the psychological and social effects of sex trafficking. While harmful effects of sex trafficking are undeniably important, the focus of this paper is to study how sex trafficking spreads across countries, to identify factors contributing to its spread, and ultimately, to determine the relative importance of these factors in order to formulate successful anti-trafficking policies.

Quantitative research and policy modeling approaches to sex trafficking has been rare due to limited data availability. Most studies avoid using quantitative methods completely and those that do not are based almost exclusively on small data samples. Based on these studies, several issues become apparent. First, accounts of trafficking in these studies often vary greatly because they focus on very specific details thus failing to see the big picture. Second, while there were some attempts to use count data in the analysis, many researchers have recognized that such approaches result in significant distortion of reality because many cases, which authorities are aware of, do not end in arrests by the police (Wahlberg and Orndahl, 2002). Finally, the spatial and geographical aspect of the environment was largely ignored in quantitative analysis, despite the fact that their importance has been recognized in theoretical discussions of this problem (Kara, 2009).

To address these issues, this paper approaches the problem differently. First, behavior of criminal groups involved in sex trafficking is complex but strikingly similar even in very diverse environments (Farley, 2007). While there are five well recognized ways (Kara, 2009) how victims become enslaved—deceit, false job offers, sale by family, abduction and recruitment by former slaves—the choice of particular method is dependent on local factors such as culture, legal system, income and gender inequality, etc. When these factors are accounted for, I show how the system traffickers operate does not differ much across regions. Second, while the reported numbers of identified sex trafficking victims reported are often not representative of the volume of the sex trade in the area, they provide invaluable information about the routes used by traffickers. Focusing on reliable data sources of known covariates and modeling traffickers' behavior in cellular automata model, I interpolate trafficking flows intensity estimates and subsequently fit the results to observed flows by adjusting relative weights of covariates thus avoiding the problems with the count data. Third, I show that the spatial and geographical aspect of the environment is of great importance. Both Kara (2009) and Brown (2000) emphasize that physical geography of an area is crucial for selection of optimal trafficking routes. Fourth, since criminal groups are often involved in more than one type of criminal activity—drug smuggling, illegal weapon trade, human trafficking—I take advantage of UN Reports on Organized Crime to determine the most likely trafficking routes. Furthermore, because criminal groups cooperate across borders, each trafficker's decision is affected by his neighbors' decisions. Finally, numerous studies identify similar environmental factors closely associated with sex trafficking that can be used as reliable covariates.

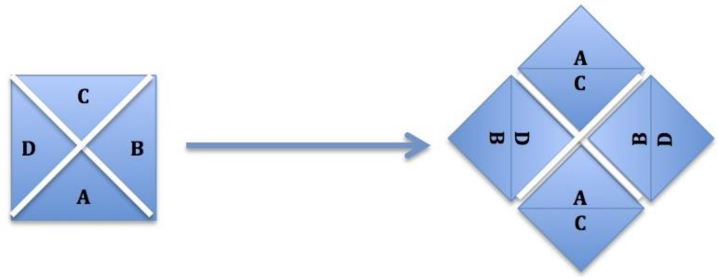
2. Data

Women's studies literature identifies a number of covariates associated with high incidence of sex trafficking. These covariates range from economic indicators through women's rights and cultural indicators to legal indicators. Additionally, I include the spatial and geographical covariates—neighboring countries, type and length of border. To construct the covariates for trafficking flow intensities, I combine data on: economic indicators (data.worldbank.org), population (data.un.org), women's rights (The World Bank, Women, Business and the Law database.), organized crime (http://www.fbi.gov/about-us/investigate/organizedcrime), cultural indicators proposed by Hofstede (geert-hofstede.com/countries.html), and type and direction of trafficking flows across countries (U.S. Department of State: Trafficking in Persons Reports, 2001–2014). Further, I take a use of descriptive information about trafficking routes discussed in Kara (2009, 2011), Brown (2000), and Farley (2007), provided by various NGOs, Trafficking in Persons Reports, and UN Reports on Organized Crime. Data is collected for 188 countries, so that I can model trafficking as a worldwide system, over period of 13 years. Due to short time period, I focus only on spatial relationships in the data. To determine the relative importance of covariates, I apply artificial neural network framework with one hidden layer, as suggested by Bishop (1995).

3. The Model of Traffickers' Behavior

To model traffickers' behavior as closely as possible and to avoid possible aggregation bias, I choose a cellular automata model. Wolfram (1983) defines cellular automata as agents, whose behavior is given by a simple set of rules but whose interactions with an environment can result in very complex behaviour. As a result, aggregate behaviour of the system can differ significantly from agent behavior at the individual level. The cellular automata model is suitable for my analysis because it can generate reasonable data flows by mimicking the actual mechanism observed.

To overcome the previously mentioned data issues, I use available information about the mechanism of trafficking observed in women's studies literature and build a cellular automata model. To demonstrate, let me use a simple toy model: The world consists of four countries, A~D (shown on the left). Each of the countries has three neighbors, for example country A has neighbours B~D.



Because the supply and demand sides of the trafficking business are quite different, I choose to model them separately. Demand in country A is defined as $Demand_A = I_A^D P_A^D$, where $I_A^D = \sum_{i=1}^{4} w_i^D X_i^D$ is an index constructed from weighted cofactor values, w_i are weights (between 0 and 1) associated with these cofactors and P_A^D is a population at risk of being trafficked within or out of country A. On the other hand, supply in country A is defined as the sum of flows into A and it consists of supplies from A and its neighboring countries, $Supply_A = \sum_{i=1}^{4} \alpha_i I_A^S P_A^S$, where α is an inverse function of income in supplier's country—suppliers from less developed countries are cheaper and therefore able to gain a larger share of the market. Finally, supply cannot exceed demand, so we have $I_A^D P_A^D \leq \sum_{i=1}^{4} \alpha_i I_A^S P_A^S$. Similar equations can be obtained for all the countries, and the system can be solved simultaneously. Note that countries only supply to a given country if the transaction is profitable.

4. Statistical Estimation of Covariate Weights

The analysis proceeds in three steps: First, relative importance of all cofactors is determined through artificial neural network estimation. Each type of trafficking flow (supply, transit, demand and internal flows) is estimated separately. To train the neural network, I split my data set onto 3 parts (at random): 60% training set, 20% cross-validation set and 20% test set. Second, I implement the cellular automata model to generate the trafficking flows, based on the most influential cofactors. The flows are estimated separately for supply and demand side of the market and for transit flows. Third, I compare the model's performance (generated trafficking flows by the cellular automata model) to observed flows in Trafficking in Persons reports (2001–2014). I select the best model based on its performance on a cross-validation set and evaluate its performance on a test set. Note that Trafficking in Persons Reports only provides descriptive information about flows; no information about levels is provided. Each country is identified as a source, transit, or destination or a mix of these types. Sometimes information on their relative size is given as well as origin and destination countries of the victims.

5. Preliminary Findings

Preliminary results of my analysis can be summarized as follows: Relative importance of cofactors associated with sex-trafficking flows varies greatly across countries, implying that there is no single magic cure-all policy that could be universally applied. When countries are grouped into clusters, based on their spatial and geographical characteristics, the relative weights of cofactors for countries within clusters become homogenous. This indicates that anti-trafficking policies should be designed with each country's spatial and geographical characteristics in mind. This conclusion is in sharp contrast with how anti-trafficking policies are currently designed: Each country is regularly evaluated and given recommendations about changes necessary to comply with one general model of policy requirements.

6. References

Becker G, 1974, Crime and Punishment: Economic Approach, in *Essays in the economics of crime and punishment*, NBER, 1-54.

Bishop C, 1995, *Neural networks for pattern recognition*, Clarendon Press, Oxford.

Brown L, 2000, *Sex slaves: The trafficking of women in Asia*. Virago, London, UK.

Cressie N, 1991, *Statistics for spatial data*, Wiley, New York, USA.

Egberg G, 2004, The Swedish law that prohibits the purchase of a sexual service: Best practices for prevention of prostitution and trafficking in human beings, *Violence against Women*, 10: 1187-1218.

Farley M, 2007, *Prostitution and trafficking in Nevada: Making the connections*. Prostitution research & education, San Francisco, USA.

Farley M, Cotton A, Lynne J, Zumbeck S, Spiwak F, Reyes M, Alvarez D, and Segzin U, 1996, Prostitution, trafficking and traumatic stress of prostitution. *Canadian Public Policy*, 22(1): 40-55.

Kara S, 2009, *Sex trafficking: Inside the business of modern slavery*. Columbia University Press, New York, USA.

Openshaw S, 1995, Commentary: Human systems modeling as a new grand challenge area in science. *Environment and Planning A,* 27, 159-164.

Rigol J, Jarvis C, and N Stuart, 2001, Artificial neural networks as a tool for spatial interpolation, *International Journal of GIS*, 15(4): 323-343.

Wahlberg K, and Orndahl C, 2002, *Situation Report 5: Trafficking in women*, Stockholm, Sweden: National Criminal Intelligence Service, National Criminal Investigation Department.

Wolfram S, 1983, Statistical mechanics of cellular automata. *Reviews of Modern Physics*, 55, 601-644.