Legal Institutions, Climate Change, and Human Trafficking*

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Abstract

While both international law and climate change researchers have how legal institutions and climate change impacts human trafficking flows in origin and destination countries, little attention is given to the "intermediary" countries through which individuals are trafficked en route to their destination. This study develops a two-part theory to explain how the effects of international legalization and climate impacts these intermediary countries. First, we argue that the diffusion of anti-trafficking laws will induce pressures on traffickers to diversify their trafficking routes. We then theorize that because climate change-induced shocks imposes costs on both states and traffickers, these costs confound the effect of legal institutions by incentivizing traffickers to shift their operations into less costly areas. Using data on human trafficking networks mined from the U.S. State Department's Trafficking in Persons Report, we analyze with statistical network analysis (1) how legalization impacts trafficking through these intermediary countries and (2) how natural shocks impact the importance of different states as preferred trafficking routes.

Keywords: climate change; human trafficking; network analysis; exponential random graph models

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Contents

1 Introduction

Climate change is recognized by many to be a defining challenge of the 21st century. According to recent reports by the International Panel on Climate Change (IPCC), it is poised to have major global impacts on numerous social aspects (Masson-Delmotte et al. 2018). One potential area of climate impact that has received surprisingly little attention is human trafficking, which is recognized by the United Nations as one of the most pernicious global challenges of the 21st century (UN General Assembly 2004). Climate change can have a compounding effect on human trafficking, as by impacting economic development and harming the livelihoods of households, it can increase the numbers of trafficking-vulnerable individuals (Bharadwaj et al. 2022), especially around the tropics (Molinari 2017; Sheu et al. 2021).

Trafficking is a complex phenomenon (International Labour Organization 2012, 2014), and as such involves not only origin and destination countries – where trafficked individuals are from and the endpoint of where they are taken – but also "intermediary" ones through which individuals are trafficked en route to their destinations (Kangaspunta 2003). Examples of intermediary states include Egypt (Van Reisen, Estefanos and Reim 2017) and India (Bharadwaj et al. 2022). The latter is an origin country and also serve as an intermediary stop for individuals trafficked from neighboring countries such as Nepal and Pakistan.

Despite the numerous connections between climate change and human trafficking, the link between climate impacts and trafficking intermediaries is non-existent in the literature. First, the existing research already pays relatively little attention to the impact of climate change on trafficking in origin and destination states (Molinari 2017), and intermediary states in general are studied even less despite their crucial importance to this inhumane process – "middleman" countries have received theoretical consideration (Akee et al. 2014), but have yet to be directly examined in empirical research. Generally, studies have sought to understand the determinants to trafficking inflow and outflow using country-level analysis (Cho 2015; Bell, Flynn and Martinez Machain 2018), gravity-type models (Hernandez and Rudolph 2015), and network analysis (Goist, Chen and Boylan 2019).

An important factor that has been considered in many studies of human trafficking flow is the presence of legal institutions designed to curb trafficking (e.g., Cho, Dreher and Neumayer 2013; Akee et al. 2014; Hernandez and Rudolph 2015). Such institutions have important implications not only in limiting trafficking in origin and destination countries – though empirical findings have thus far been mixed – but also in creating stronger limitations on trafficking in intermediary states. Notably, there has been a rapid international diffusion of anti-trafficking laws over the last two decades. Since 2000, roughly 75% of countries have established anti-trafficking laws, compared to less than 10% that did so before 2000 (Sim-

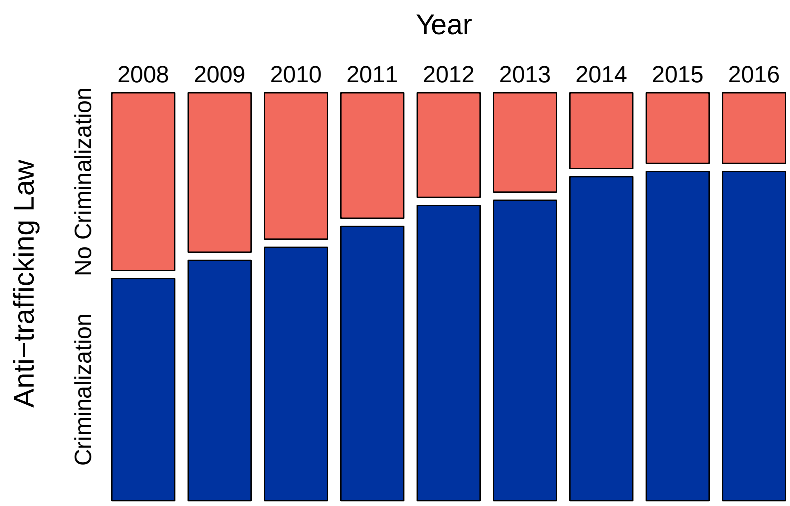

Figure 1: Annual Proportion of Countries with Anti-trafficking Law, 2008–2016

mons, Lloyd and Stewart 2018). Existing research has attributed the rapid expansion of the anti-trafficking legal regime to the diffusion of liberal policies, social globalization, or the avoidance of negative externalities (e.g., Cho 2013; Simmons, Lloyd and Stewart 2018), all of which imply there are important strategic interdependencies, e.g., anticipation effects, in how states behave with regard to human trafficking. In turn, there should be complex downstream effects on human trafficking patterns as traffickers respond to these legal institutions, such as attempting to evade anti-trafficking institutions through diverging trafficking routes.

However, the downstream complexities of the diffusion of the international anti-trafficking regime have yet to be explicitly examined in quantitative analysis of trafficking patterns. Gravity-type models and network analysis start to get at important dyadic factors of trafficking flows, and network analysis in particular is able to capture system level dependencies in trafficking patterns, but existing studies generally remain focused on trafficking origins and destinations and flows between them (Goist, Chen and Boylan 2019), where the analysis of route divergence and trafficking spread is difficult. We address these gaps in the human trafficking literature by examining how climate impacts change human trafficking patterns with an emphasis on how it moderates the relationship between anti-trafficking laws adoption and trafficking patterns in intermediary countries. As we show below, in addition to being substantively important, these countries are well-suited for studying the impact of different factors on trafficking routes.

We ask two related questions about the interplay between climate impacts and legal institutions on trafficking routes. First, what has been the impact of anti-trafficking law diffusion on the divergence of trafficking routes? As we discuss in detail below, because anti-trafficking law adoption tends to diffuse across countries (Simmons, Lloyd and Stewart 2018), it creates a more complicated landscape for traffickers, and therefore increases divergence in intermediary countries as traffickers are pressured to "diversify" their routes to minimize the effects of these laws. Second, how has climate change shaped the impact of these anti-trafficking laws? We suggest that by increasing the frequency of shocks from natural hazards and disasters, climate change works as a *confounder* to the impacts of legal diffusion. Given the scale of some natural shocks, they can impose massive costs on institutions (Koubi 2017; Schon, Koehnlein and Koren 2023) – both formal legal ones and those serving the "shadow economy" that human traffickers operate in (Naim 2010) – leading to shifts in the previously established balance between governance institutions and traffickers. We expect one of two outcomes to occur. All else equal, when (1) natural shocks impose greater costs to traffickers than to state institutions, trafficking should decrease in disaster impacted states, thereby reducing route divergence, but proceed as normal in alternative intermediaries that are not exposed to these shocks; and, conversely, when (2) natural shocks impose greater disruptions to state capacity than to trafficking routes, it attenuates the diversionary effects of legal institutions across all adopting states because traffickers will take advantage of the situation by seeking to concentrate resources through the climate impacted ones.

To answer our questions, we conducted a comprehensive evaluation of trafficking and climate change using new combined tools in machine learning and network analysis. Using data on human trafficking networks created with machine learning tools from Trafficking in Persons (TIP) reports from the U.S. State Department by Goist, Chen and Boylan (2019), we tested the impact of anti-trafficking laws and natural shocks on real trafficking flows and network structures using the exponential random graph model, which has been previously used to study human trafficking (Goist, Chen and Boylan 2019) and other illicit trade networks (Aziani, Berlusconi and Giommoni 2021; Norbutas 2018). First, we tested whether and how anti-trafficking laws impact trafficking patterns, focusing on the potential for route divergence through intermediary states. Second, we evaluated how shocks from natural hazards and disasters shape criminalization-based route divergence.

Our analysis speaks to important notions from both the theoretical literature and policy applications. First, we find that trafficking routes tend to be diverted among multiple countries that have adopted anti-trafficking laws, but more concentrated where criminalization has yet to occur. In doing so, we offer direct evidence for an important downstream implication of legal institutions' tendency for diffusion (Simmons, Lloyd and Stewart 2018). By complicating the landscape in which traffickers operate, the diffusion of anti-trafficking laws has, indeed, induced divergence in trafficking routes. We also find that this pattern has become highly contingent on the rate of natural shocks in more recent years – a temporal trend that is in line with the logic that climate change has increased the frequency of natural disasters over the period (Zeng et al. 2023). Specifically, since 2011, trafficking patterns running through states that have passed anti-trafficking laws differed by whether the states have recently been exposed to natural shocks; and since 2013, which is when the number of states that have yet to criminalize trafficking has stabilized to under 30 as shown in Figure 1, route divergence among intermediaries criminalizing trafficking that are impacted by natural shocks drops to the same level as non-legislating intermediaries (which as a group do not appear to be impacted by natural shocks). Our findings suggest that shocks from natural hazards and disasters tend to be more disruptive to traffickers than to states' legal institutions, as these patterns are indicative of traffickers leaving shock-disrupted intermediaries rather than converging on them. While we are agnostic as to whether the impact of these dynamics on trafficked humans is positive or negative, we conclude that climate change may confound the effect of legal institutions in susceptible states.

2 Anti-Trafficking Legalization, Natural Shocks, and Climate Change

Research on human rights and democratization finds that such processes often happen by the way of increasingly more frequent adoption through issue or physical proximity, a process often called "diffusion" (Greenhill 2010, 2015). Diffusion is a key process in international politics, as "the decision to liberalize (or restrict) by some governments influences the choices made by others" (Simmons and Elkins 2004, 171-172), meaning that policies can clustering in time and space, often rapidly cascading through the entire global system. Previous studies have shown that diffusion underlies multiple areas of human rights and their international adoption by states, including labor rights (Greenhill 2010), economic liberalization (Simmons and Elkins 2004), anti-terrorism (Josua 2021), and – our focus – human trafficking criminalization (Simmons, Lloyd and Stewart 2018).

2.1 Legal Institutions Diverge Trafficking Routes

An important aspect of diffusion is that it can be driven by policy competition. Such competition can create intense pressures to adopt these policies to address potential externalities resulting from policy adoption by neighboring states. This issue is especially relevant when anti-trafficking legislation is concerned. As Simmons, Lloyd and Stewart (2018, 251) explain:

> "When one state criminalizes human trafficking, its neighbors anticipate that trafficking will be diverted to their own jurisdictions, along with the associated

> violence, fraud, illegal immigration, and drug/weapons smuggling assumed to be associated with transnational organized crime. Viewed in this context, criminalization policies are essentially 'contagious,' since the potential exists for enforcement in one country to divert transnational criminal activity elsewhere."

Accordingly, the adoption of an anti-trafficking policy in one state makes is more likely its neighbors will adopt similar policies to prevent potential spillovers of traffickers and trafficked individuals into its own territory.

The logic of anti-trafficking law diffusion has implications for trafficking intermediaries as well. Just like sending and receiving states, intermediaries may adopt anti-trafficking laws. For instance, Egypt – a key intermediary for individuals trafficked from the Horn of Africa and Eastern Europe into Israel, but rarely the beginning or end point of trafficking – has approved anti-trafficking laws based on the Palermo protocols in 2010 (Mattar 2011; Awad 2023). When an intermediary state adopts anti-trafficking legislation, which raises the costs of trafficking through that country, it should induce other substitutable intermediaries to also criminalize trafficking to avoid the negative externalities of being among the non-criminalizing state that trafficking paths instead converge through. In adopting anti-trafficking legalization, adopting states, including intermediaries, change the trafficking landscape, creating new hurdles for traffickers and raising the costs they incur.

When more intermediaries adopt anti-trafficking laws, traffickers either are pressured to find alternative ways to continue trafficking humans across criminalizing countries or shift their routes to countries that have yet to adopt similar laws (Simmons, Lloyd and Stewart 2018). In the former scenario, the need to diversify trafficking routes to diffuse risks from criminalization leads to divergence of trafficking through multiple criminalizing intermediaries, which offers a plausible explanation for the generally mixed findings on the impact of criminalization on trafficking inflows (e.g., Cho, Dreher and Neumayer 2013; Akee et al. 2014; Hernandez and Rudolph 2015). In the latter scenario, where there are suitable alternatives that have yet to criminalize trafficking, trafficking routes should converge on them. Because of both the smaller number of non-criminalizing alternatives and the lack of the incentives to diverge paths among them, trafficking through non-criminalizing intermediaries is more likely to converge on a smaller number of alternatives.

These evasive manoeuvres are not mutually exclusive, and traffickers likely adopt a mix depending on the combination of criminalizing and non-criminalizing states they operate in. This link between the criminalization of trafficking and path divergence, which builds on the implications from Simmons, Lloyd and Stewart (2018), suggests our first pair of complementary hypotheses:

- **H1a:** *For intermediary states that have adopted anti-trafficking laws, there will be greater divergence of trafficking paths through multiple intermediaries.*
- **H1b:** *For intermediary states that have not adopted anti-trafficking laws, trafficking paths are more likely to converge on a smaller number of intermediaries.*

2.2 Natural Shocks Confound Legal Institutions

Next, we consider the impact of natural hazards and disaster shocks on the relationship between anti-trafficking legal institutions and human trafficking routes. Importantly, many origin and intermediary trafficking states – e.g., Libya, Egypt, Lebanon, Burundi, Bangladesh, Cambodia, Panama, and Colombia – are located in the tropic and subtropic regions of the globe (UNODC 2009). In addition to exhibiting higher trafficking risk, these regions are also highlighted by the IPCC as the most susceptible to climate change and its effects (Masson-Delmotte et al. 2018), including, natural shocks such as floods, storms, droughts, and heatwaves, which are expected to intensify over time (Allan et al. 2020; Tabari 2020; Ginesta et al. 2023). These shocks are generally destabilizing to local institutions, but can have different impacts on state governance institutions and illicit trafficking institutions.

Cost to Traffickers It is likely that having to deal with the impacts of floods and heatwaves, among other shocks, strongly increases the costs of trafficking, especially across borders (Gurung and Clark 2018). Traffickers often operate in a "shadow economy" (Naim 2010) that are generally costly to maintain due to the need to circumvent legal regimes (Early and Peksen 2020; Choi and Thum 2005). Natural shocks can compound existing trafficking costs (Raddatz 2009), for instance, via destroying infrastructure (thereby forcing traffickers to unexpectedly move individuals over longer distances and around affected areas), which can turn such shocks into protracted disasters (Cappelli, Costantini and Consoli 2021); increasing moving times (traffickers have to hold the individuals in different locations longer periods of times while they are waiting for a flood or a storm to clear); and creating a need for general adaptation (Dolšak and Prakash 2018), such as having to construct more shelters or invest in other disaster preparedness measures.

If the costs of countering these natural shocks mount, traffickers may choose to divert their illicit activities from these impacted areas, instead converging among alternatives that have not been impacted. For trafficking operations that primarily take place among a set of intermediaries that have already adopted anti-trafficking laws, this means traffickers will focus on investing in maintaining routes across the set of intermediaries not impacted by natural shocks rather than maintaining route diversity across all alternatives.

Cost to States Shocks from natural hazards and disasters also impose costs on states, especially as many states susceptible to climate impacts also suffer from limitations in state capacity (Koubi 2017). Natural shocks may limit states' ability to operate in affected areas (Von Uexkull et al. 2016); disruptions from natural shocks also open the door for corruption and abuse of resources by officials (Fredriksson and Neumayer 2016); and prior work has further shown that in regions susceptible to climate impacts (e.g., the Kenyan drylands after droughts), households and individuals may be more likely to engage in illicit activity and contest authority (Mosberg and Eriksen 2015; Vestby 2019). As such, natural shocks often force states to reallocate resources to deal with the resulting impacts, especially if shocks deteriorate into a local or national disaster (Cappelli, Costantini and Consoli 2021; Schon, Koehnlein and Koren 2023).

Increasing rates of severe natural shocks therefore mean adverse impact to the state's ability to monitor trafficking and enforce its legal regime against it, which makes these climate impacted states more desirable for traffickers. When the balance shifts enough in the traffickers' favor, they will be incentivized to move their operations into these affected regions. In cases where traffickers had otherwise diversified their operations among multiple intermediaries that have adopted anti-trafficking laws, the presence of a natural shock in a subset of those states will make it more likely that trafficking paths converge on that subset.

Greater rates of natural shocks can work to confound the effect of legalization in highly climate change susceptible states, as it can cause shifts in the established balance between governance institutions and traffickers. Considering the costliness of natural shocks on both legal governance institutions and illicit trafficking institutions, we expect increasing natural shocks to moderate the observed relationship between the criminalization of trafficking and trafficking route divergence in one of two ways – depending on the relative cost of natural shocks to states and to traffickers – which we explore as an open research question: (1) If natural shocks impose greater costs to traffickers than to state institutions, trafficking should decrease in disaster impacted intemediaries and remain at normal levels in intermediaries that criminalize trafficking but are not exposed to natural shocks; conversely, (2) if natural shocks impose greater disruptions to state capacity than to trafficking routes, there will be strong incentives for traffickers to seek gains by concentrating resources through impacted states, decreasing route divergence in both impacted and unimpacted states. This suggests the following conditional hypothesis and accompanying research question:

- **H2:** *Natural shocks will confound the path diverging effect of anti-trafficking laws on adopting intermediaries.*
- **RQ:** *Which types of states will the confounding effects of natural shocks incentivize*

traffickers to converge on?

3 Empirical Approach

Our aim in this paper is to study the generative features that underlie the transnational human trafficking, with a particular focus on the role of legal institutions and climate shocks and disasters in intermediary trafficking countries. To do so, we use annual transnational human trafficking network data constructed by Goist, Chen and Boylan (2019) using text from the Trafficking in Persons (TIP) report published by the U.S. Department of State. We study the network using the exponential random graph model (ERGM), a statistical model designed for inferential network analysis (Cranmer and Desmarais 2011).

3.1 Measurement

3.1.1 Trafficking Network Construction

Goist, Chen and Boylan (2019) developed an entity recognition and machine learning classifier approach to extract human trafficking patterns between countries from qualitative data in the U.S. State Department's Trafficking in Persons (TIP) report, which is published annually. They applied their algorithm to TIP reports from 2001–2016 and publicly released the data as directed dyads of countries identified in each annual report as senders and receivers of human trafficking. We only selected the 2009–2016 data because it is the period for which the TIP reports include comprehensive and granular information about trafficking patterns. First, the pre-2009 raw trafficking data are limited to only 83 countries that were deemed to have had a "significant number" (i.e., 100 or more) of victims. Starting in 2009, the scope of the TIP assessment process was broadened to encompass all nations involved in origin, transit, or destination rather than solely focusing on those with 100 or more reported trafficking victims (Gallagher 2011, p. 383). In 2017, the TIP report expanded their documentation period to the most recent five years, which makes it difficult to determine what happened in the reporting year. To bound the system so we can generate a network of human trafficking, we used country data from the Correlates of War and removed countries with a population of less than one million. We ended up generating a directed network of human trafficking that has 154 countries.

3.1.2 Legal Institutions and Natural Shock Exposure

To measure criminalization of human trafficking in domestic law, we used the data set collected by Simmons, Lloyd and Stewart (2018). Countries are considered to have criminalized human trafficking, as a binary measure, if they have enacted specific anti-trafficking legislation with broad coverage and no significant exceptions (Simmons, Lloyd and Stewart 2018, 261). We incorporated the criminalization of human trafficking data from 2008 to 2015 into our nodal attribute data set. These years match the TIP reports from 2009–2016 because each year's reporting period covers the twelve month period from April of the previous year to March of the current year. As we outline in detail in the appendix, we made a number of small adjustments to add missing countries or missing laws.[1]

To measure natural shock exposure, we used the geophysical, meteorological, hydrological, climatological disasters data from EM-DAT (2023). Again, due to the TIP's non-calendar year reporting period, we use data from 2008–2015. We counted the total natural shocks of these types for a country and constructed a binary measure of exposure or not. Prior to binarization, the mean value of the total natural shock exposure count is 2.33, with a minimum of 0 and a maximum of 43, which was China in 2013.

3.2 Statistical Modeling for Networks

To model the transnational human trafficking network, we use the exponential random graph model (ERGM), which has been used to study a wide range of phenomena in international politics (e.g. Cranmer, Heinrich and Desmarais 2014; Leifeld and Fisher 2017; Windzio 2018; Thurner et al. 2019), including human trafficking (Goist, Chen and Boylan 2019). The ERGM is a statistical model that allows for inference on tie formation in relational systems (i.e. a network). In such systems, observed outcomes are not independent of one another. Instead, what happens in one dyad depends on other dyads, rendering traditional logistic regression models prone to omitted variable bias and underestimated standard errors (Cranmer and Desmarais 2016). As empirically demonstrated previously, global human trafficking patterns is one such system (Goist, Chen and Boylan 2019), which we corroborate in our analysis.

The ERGM addresses the issues of fitting networked systems with dyad-independent models by considering the entirety of observed ties and non-ties as a draw from a multivariate distribution, which allows tie formation to depend on factors beyond the dyad (Cranmer and Desmarais 2011). More specifically, in the ERGM, the probability of observing the network $\boldsymbol{Y}$ is a function of factors at the node, dyad, and hyperdyad levels (i.e., two or more linked dyads, Cranmer and Desmarais 2016). Explicitly, the model is

$$Pr(\boldsymbol{Y}, \boldsymbol{\theta}) = \kappa^{-1} \exp\{\boldsymbol{\theta}' \boldsymbol{h}(\boldsymbol{Y})\} \tag{1}$$

[1] North Korea, Serbia, South Sudan, Taiwan, and Timor-Leste; and Singapore's 2014 Prevention of Human Trafficking Act.

where $\boldsymbol{\theta}$ is a vector of coefficients and $\boldsymbol{h}(\boldsymbol{Y})$, effectively the model terms, is a vector of statistics computed over $\boldsymbol{Y}$. κ is the normalizing constant that makes the equation a probability density function.

In an ERGM specification, a model term is usually a raw or weighted count of local network configurations (i.e., specific combinations of ties over a set of nodes) that should be observable if the hypothesized effect is part of the system's generative process that governs tie formation in the network. When looking at a conflict network, for example, the dyadic democratic peace effect would be captured by a low number of joint democracy dyads that have conflict ties. As noted, the local configurations used to model tie formation are importantly not limited to the node level or the dyad level. Instead, they can include as many dyads as necessary to capture the conceptualized generative feature. For example, to account and test for the popularity effect – the notion that nodes with incoming ties are likely to get more incoming ties – researchers could include a model term that is the count of 'two-stars' (i.e. $i \to k, j \to k$) in the network, which lets the probability of tie formation on $i \to k$ to depend on the existence of $j \to k$, and vice versa.

3.2.1 Modeling Diffusion of Trafficking

The logic of ERGM specification being based on local configurations extends to more complex generative features. In our present examination, our main focus is on (1) the tendency for trafficking paths to diverge when trafficking is criminalized, and (2) the impact of climate change and other natural shocks on this trend. As we discussed above, the first expectation is based on Simmons, Lloyd and Stewart (2018), who posed a policy-diffusion model for the adoption of legislation criminalizing human trafficking based on the spread of negative externalities. Specifically, they argued that when a country criminalizes human trafficking, neighbouring countries are more likely to do the same because they expect trafficking flows to be redirected to less costly (i.e., non-criminalized) paths.

To study this, we focus on trafficking patterns where flows between origin and destination countries run through intermediary transition countries because path divergence is most explicitly observable in these instances, assuming that origins and destinations are *non-substitutable*. Our expectation is that when substitutable intermediary countries $h_{1 \ldots k}$ criminalize human trafficking, the number of trafficking paths between a pair of origin i and destination j countries should become greater, i.e., that it should involve more of these intermediary countries.

We illustrate this concept in Figure 2. When no country has criminalized trafficking as in (a), flow should be directed through a smaller number of alternative paths based on trafficking preferences. In this illustration, all trafficking activity is channeled through the most clearly desirable h_2. If, as in (b), h_2 passes legislation criminalizing trafficking (indicated by gray shading), traffickers will find h_2 less desirable than before, and divert their activities through either or both of the alternatives. Based on the negative externalities policy diffusion model (Simmons, Lloyd and Stewart 2018), h_1 and h_3 should also criminalize trafficking as in (c), because they anticipate trafficking diverted away from h_2. If this happens, our expectation as described above is that traffickers will be pressured to diversify trafficking routes across multiple alternatives to diffuse risk.

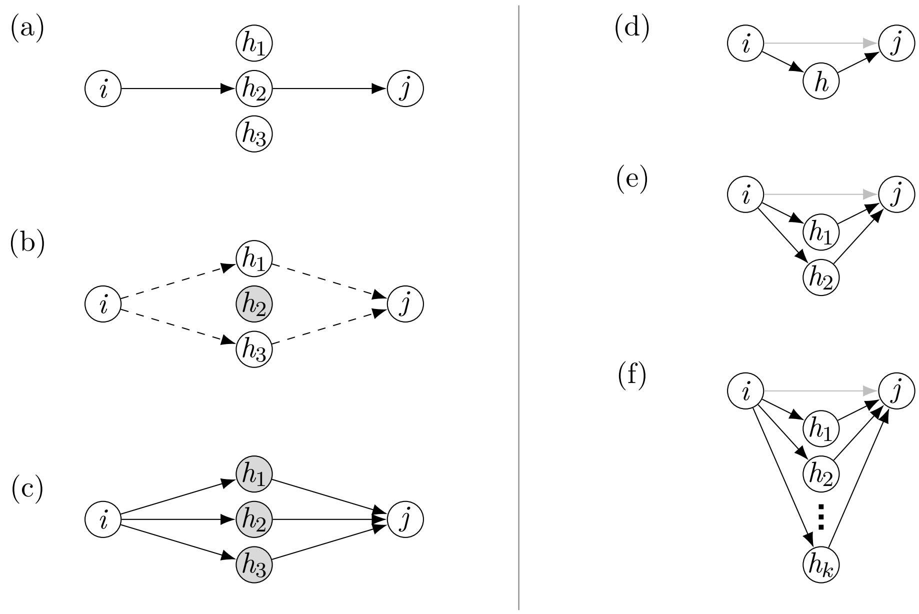

Figure 2: (a)–(c) illustrates that as substitutable intermediary countries criminalize trafficking (highlighted in gray), trafficking flows have a tendency to become more diffuse compared to being directed through a smaller number of non-criminalizing countries. (d), (e), and (f) show ordered pairs (i, j) with one, two, and k transitive shared partners. The gray directed tie from $i \to j$ indicates that the GWDSP statistic is computed over all ordered pairs (i, j) regardless of whether a tie exists.

In an ERGM, this kind of path divergence can be modeled as a generative feature by including terms based on "transitive shared partner" statistics, which in network terminology refers to nodes that sit on paths of length two running between ordered pairs of nodes, such as the h nodes in Figure 2. Explicitly, for an ordered pair (i, j), h is their transitive shared partner if there is a two path running from i to j through h (i.e. $i \to h \to j$). Figure 2 shows configurations with (i, j) sharing (d) one, (e) two, and (f) k transitive partners.

Among transitive shared partner statistics, the *geometrically weighted dyadwise shared partner* (GWDSP) statistic is particularly relevant to our examination because it captures the tendency for structural equivalence in the network (Goodreau 2007). This statistic is based on the weighted sum of the distribution of transitive shared partner counts over all ordered

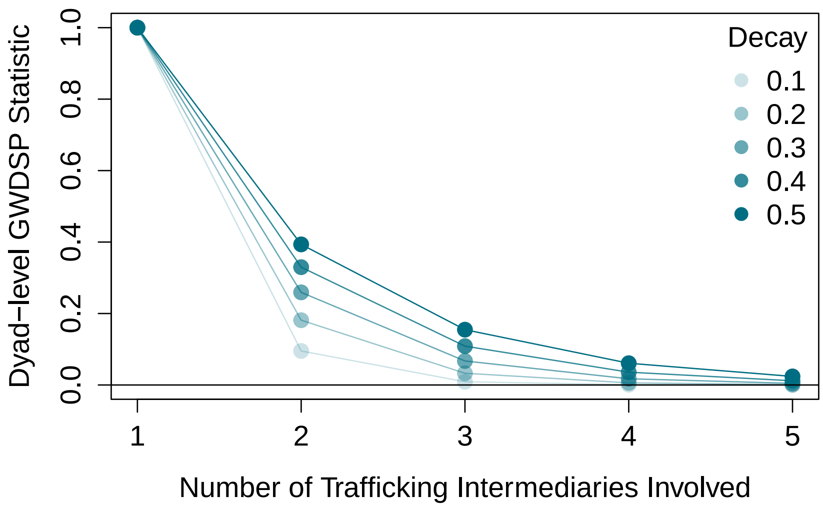

Figure 3: The GWDSP statistic at the dyad level as the number of trafficking intermediaries increase, shown across different levels of the downweighting decay parameter. Higher levels of the decay parameter applies a lower level of downweighting on each successive intermediary involved.

pairs in the network.[2] Because it considers all k-transitive shared partners where $k \geq 1$, the GWDSP represents the tendency for multiple nodes to occupy structurally equivalent positions in the network (i.e., as transitive shared partners $h_{1...k}$ of ordered pairs (i, j) as shown in Figure 2).

We can more explicitly see how the GWDSP term governs the tendency for structural equivalence in network paths by considering the ERGM in terms of tie formation over a collection of dyads rather than the equivalent model of the whole network, which is a well-known feature of the ERGM (Goodreau, Kitts and Morris 2009). In this formulation, the probability of observing a tie on a given dyad depends on whether that dyad is part of local network configurations corresponding to model terms of interest. For the GWDSP, the configurations are one-or-more two paths connecting any ordered pair, which we illustrate in the right-hand panel of Figure 2. This means that the probability of $i \to h_1$, for example, depends on whether (i, h_1) is part of a configuration that has an existing $h_1 \to j$ tie, and on how many other existing $i \to h_k$ and $h_k \to j$ two paths also connect i and j.[3]

The constellation of ties in its local neighborhood determines how many GWDSP configurations – and of what k – each dyad is part of, and therefore the value of the GWDSP statistic for that dyad. With the geometric-weighting on the additional partners h_k, the larger the number of two paths connecting (i, j), the lower the value of (i, h_1) for the GWDSP statis-

[2]The GWDSP statistic is obtained with $e^{\theta} \sum_{k=1}^{n-2} \{1 - (1 - e^{-\theta})^k\} DP_k(\boldsymbol{Y})$, where $\boldsymbol{Y}$ is the network, n is the size of $\boldsymbol{Y}$, $\theta \geq 0$ is decay parameter determined based on model fit, and DP_k is a function that yields the count of the ordered pairs in $\boldsymbol{Y}$ that has k transitive shared partners (Hunter 2007, eq. 26).

[3]Equivalently, the probability of $h_1 \to j$ depends on the existence of $i \to h_1$ and other $i \to h_k$ and $h_k \to j$ two paths.

tic. We illustrate this in Figure 3. Because each additional shared partner h_k (and therefore ties from $i \rightarrow h_k$ and $h_k \rightarrow j$) means all dyads in the configuration have a lower value of the GWDSP statistic compared to if the configuration had only $k-1$ shared partners, a positive coefficient means ties have a tendency to form where k is low (with the highest tendency at $k = 1$), which is the opposite of path divergence.[4] Conversely, this means conditional on a trafficking path being formed to an intermediary (or from an intermediary), *a negative coefficient on the GWDSP term should be interpreted as the tendency for $i \rightarrow h_k$ (and $h_k \rightarrow j$) to form where k is high, and hence for an ordered pair (i, j) to have many shared partners* (i.e. for structural equality or path divergence). This logic has been shown elsewhere for the geometrically weighted version of the degree distribution (Levy 2016).

3.2.2 Conditioning Intermediary Diffusion on Intermediary Characteristics

With this in mind, to examine the effects of criminalization diffusion and the confounding potential of natural shocks on trafficking route divergence, we extend the GWDSP statistic by limiting the counted transitive shared partners based on whether they have criminalized trafficking and experienced natural shocks. Conceptually, this can be understood as interacting *tendency for structural equivalence* with *country-level factors*. By including both the GWDSP term conditional on criminalization of trafficking and on the existence of natural shocks, we are able to test whether countries that have criminalized trafficking end up in more structurally similar positions in the trafficking network, and whether experience with natural shocks attenuate this pattern.

Specifically, we fit the models described in Table 1 for each year from 2009–2016 in TIP reporting years, starting with a model that includes no network terms (model 0), following by a model that includes network terms without accounting for diffusion (model 1), then a network diffusion model of anti-trafficking legalization (model 2), and finally two model that accounts for the impact on natural shocks in this network diffusion model (model 3 which allows shocks to affect states that have anti-trafficking laws, and model 4 which allows shocks to affect states that have no anti-trafficking laws). To test our hypotheses, we compare successive models against its preceding baseline – i.e., model 1 to 0, 2 to 1, and both 3 and 4 to 2 – using the Bayesian Information Criterion (BIC) model fit statistic, which adjudicates between models based on likelihood while penalizing additional complexity. We use this measure to assess whether the parameters added based on our theoretical expectations better explain the observed phenomena. The first comparison, which compares models

[4] More technically, the dyad-level statistic of the GWDSP term for (i, h) or (h, j) when considering only one ordered pair (i, j) is some value in $[0, 1)$ (depending on the downweighting parameter) exponentiated by the number of (i, j)'s shared partners not counting h (Snijders et al. 2006, eq. 27), meaning as the number of shared partners increase for a given dyad, the lower the observed value for that dyad.

Table 1: Summary of Variables and Model Terms.

Model Term	Data Source	M0	M1	M2	M3	M4
Contiguity	CEPII	•	•	•	•	•
Distance	CEPII	•	•	•	•	•
Electoral Democracy	V-Dem	•	•	•	•	•
GDP per capita	World Bank	•	•	•	•	•
Gini Coefficient	WID	•	•	•	•	•
Population	World Bank	•	•	•	•	•
State Fragility	CSP	•	•	•	•	•
Unemployment	World Bank	•	•	•	•	•
Women Civil Liberties	V-Dem	•	•	•	•	•
Trafficking Criminalization	Simmons et al.	•	•	•	•	•
Natural Shock Exposure	EM-DAT	•	•	•	•	•
Edges (Intercept)	-	•	•	•	•	•
Reciprocity	-		•	•	•	•
GW indegree	-		•	•	•	•
GW outdegree	-		•	•	•	•
GW edgewise shared partner	-		•	•	•	•
GWDSP (decay = 0)	-		•	•	•	•
GWDSP (all)	-		•			
GWDSP (w/ Law)	-			•		•
GWDSP (w/o Law)	-			•	•	
GWDSP (w/ Law, w/o Disaster)	-				•	
GWDSP (w/ Law, w/ Disaster)	-				•	
GWDSP (w/o Law, w/o Disaster)	-					•
GWDSP (w/o Law, w/ Disaster)	-					•

with and without hyperdyadic network terms, shows whether the ERGM is justified over the more parsimonious logistic regression. The second comparison, based on whether the model conditions trafficking intermediaries by whether they have criminalized trafficking, assesses our interpretation of Simmons, Lloyd and Stewart (2018), specifically whether diffusion of legal institutions impacts trafficking patterns. Finally, the third and fourth comparisons, which further conditions intermediaries that have criminalized or not criminalized trafficking by whether they are exposed to natural shocks, assesses the need to consider the effect of climate change when studying the impact of legal institutions on illicit behaviors.

3.2.3 Other Model Terms

As Table 1 shows, we also include other dyadic and nodal attributes in our data set. For the dyadic attribute, we collect data regarding contiguity and geographic distance based on

CEPII's GeoDist dataset (Mayer and Zignago 2006) and trade value in US dollars according to the IMF's Direction of Trade Statistics on trade exports (IMF 2023). For the nodal attributes of each country, we include the Electoral Democracy and Women's Civil Liberties from V-Dem (2023), GDP per capita, Population, and Unemployment from the The World Bank (2022), Gini Coefficient from World Inequality Database (2023), State Fragility from the Center for Systemic Peace (CSP) (Marshall and Elzinga-Marshall 2017).

We also included additional hyperdyadic network terms that are common to statistical network models. Reciprocity captures the tendency for sending relationships between two countries to be mutual. The geometrically-weighted in- and outdegree terms provide a better fit of the network's degree distribution. The geometrically-weighted edgewise shared partner term captures the tendency for clustering. Finally, the GWDSP term with a decay parameter of 0 conditions whether an edge is sent to or from a single intermediary, which is required to interpret our focal GWDSP terms (with non-zero decay) as governing whether intermediary divergence occurs.

4 Results

In estimating our models,[5] we first find that across all years, Model 1, the baseline network model, greatly outperforms Model 0, the dyad-independent model, by BIC values ranging from 149.3–336.4, indicating that including hyperdyadic network components greatly improves our modeling power of this complex international phenomenon, which adds further evidence to the body of work showing that global human trafficking is an interdependent relational system (e.g., Goist, Chen and Boylan 2019; Simmons, Lloyd and Stewart 2018).

Moving to our substantive examinations, we find evidence for both of our hypotheses. First, we expand the baseline network model by conditioning the GWDSP term on whether the trafficking intermediaries have criminalized trafficking. This allows us to examine whether and how trafficking through intermediaries systematically varies by those countries' legal institutions. As shown in Figure 4 (top panel) with annual coefficient estimates for the conditional GWDSP terms, we find that, from 2009–2014, trafficking ties forming two paths are less likely to be deterred from divergence when shared partners on the two path (i.e., intermediaries) have adopted anti-trafficking laws compared to when they have not. This indicates that conditional on all other modeled factors (including baseline sender and receiver effects for trafficking criminalization and hazards exposure for all countries), we are more

[5] Estimation was done in R with the ergm and multilayer.ergm packages. We used simulated annealing to set starting values for the MCMC estimation (Schmid and Hunter 2024). As discussed above, the GWDSP term has a downweighting parameter. We report main results from models using decay = 0.5, but our findings are robust to a reasonable range of this parameter (i.e., 0.1–0.5).

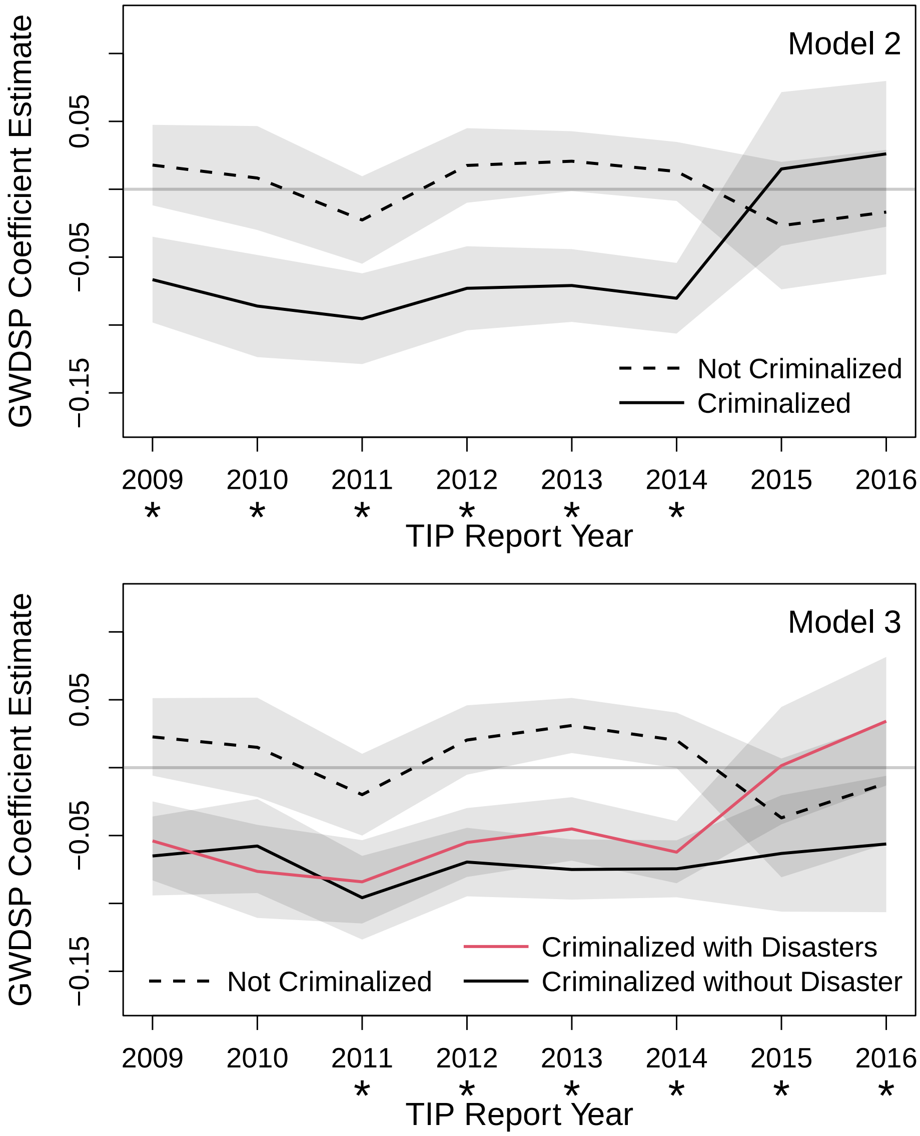

Figure 4: Coefficient estimates for various conditional GWDSP terms. The shading shows 95% confidence intervals around the point estimates. Asterisks indicate the plotted model outperforms its immediate predecessor (see Table 1) in terms of BIC.

likely to observe countries to have more intermediaries that have criminalized trafficking than those that have not. The difference in coefficient estimates is reflected in the model fit statistics, as Model 2's BIC meaningfully outperforms that of Model 1 in the years 2009–2014.

Based on Model 2, the difference between these two sets of countries ostensibly vanishes in 2015 and 2016 as trafficking paths were no longer more likely to diverge across states with anti-trafficking laws. This brings us to our next examination in Model 3, where we further expand the GWDSP terms by conditioning intermediaries that have criminalized trafficking by whether they have been exposed to climate shocks in the given year. This gives us three

GWDSP coefficients to consider, which we show in Figure 4 (bottom panel). Looking first at model fit, we see that while the tendency for diverging trafficking paths appear to be similar in Models 2 and 3 from 2009–2014, Model 3 starts to outperform Model 2 in 2011, meaning that there is a significant difference in the tendency for trafficking path divergence based on states' exposures to natural shocks.

The years for which Model 2 does not outperform Model 1 (2015–2016) are also the years that Model 3's GWDSP coefficients for states with and without anti-trafficking laws start to become visually distinct from each other. This suggests that legal institutions became confounded by natural shocks on the system. This is supported by the GWDSP coefficient estimates. Whereas the pre-2015 tendency for trafficking paths to diverge through intermediaries criminalizing trafficking now decreases when these states are exposed to natural shocks, the pattern of divergence remains for those not exposed to these shocks.

These patterns also address our open research question about how exactly the natural shocks tends to shift the balance between states' legal institutions and human traffickers. Our findings suggests that states tend to be more resilient to these shocks than are traffickers, as our evidence indicates that traffickers are moving out from shock exposed areas while maintaining their operations in nonexposed areas rather than shifting all their resources toward afflicted areas.

Finally, extending this treatment to intermediaries that have not criminalized human trafficking (i.e., Model 4) does not yield systematic improvements in model fit, likely due to the small number of countries that have neither criminalized human trafficking nor been exposed to natural hazards, especially as most states have adopted anti-trafficking laws toward the end of our observation period (Figure 1).

5 Discussion and Conclusion

In this study, we sought to achieve two goals. First, we wanted to test the impact of diffusive legalization, as hypothesized, e.g., by Simmons, Lloyd and Stewart (2018), is valid when intermediary traffickers are concerned. As Figure 4 (top plot) shows, we find that, indeed, this is the case: the adoption of anti-trafficking laws in intermediate countries has created a noticeable divergence of trafficking routes in contrast to countries that did not adopt similar legal measures. Second, we sought to evaluate the impact of climate change – and specifically, natural shocks, the rate of which is expected to increase due to climate change (e.g., Allan et al. 2020; Ginesta et al. 2023; Tabari 2020) – on anti-trafficking legalization. We find that, a Figure 4 (bottom plot) illustrates, natural shocks confound the effect of anti-trafficking legalization in intermediary states, suggesting these confounding effects might intensify in the future.

For researchers, in line with past studies (e.g., Simmons and Elkins 2004; Greenhill 2010, 2015; Simmons, Lloyd and Stewart 2018), our results first suggest that international legalization indeed spreads through a diffusive process, and that this can have clear and observable real-world implications on the behaviors the legalization is expected to target. Explicating how anti-trafficking legalization shifts trafficking behaviors therefore opens doors into better theorizing and modeling the calculations traffickers and other international low violators make, increasing our understanding of these behaviors and – ultimately – facilitating the creation of better prevention efforts.

The results also illustrate how climate change can impact international legal institutions by shifting the balance of state capacity and nonstate actor behaviors. This can assist in creating a more comprehensive research frameworks on the potential cross-national social and political impacts of climate change, reducing some of the uncertainty surrounding these issues, and opening doors for additional inquiries into similar areas of related international human rights legalization and economic activities. More generally, our findings add to the body of evidence showing that improving our understanding of complex international relations phenomena is greatly improve by incorporating network-based approaches (Cranmer and Desmarais 2016). Indeed, our ability to quantify the impact of both legalization and climate change in these regards is directly dependent on a combination of text analysis and network modeling. This provides an illustration as to how these methods can assist in creating more detailed research frameworks that are necessary to address new international challenges, which involve indirect dynamics and nonstate actors.

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