Interdiction Models to Disrupt the Operations of Sex Trafficking and Other Forced Illicit Labor Networks

Michael T. Clark
mtc3@g.clemson.edu

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INTERDICTION MODELS TO DISRUPT THE OPERATIONS OF SEX TRAFFICKING AND OTHER FORCED ILLICIT LABOR NETWORKS

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
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Master of Science
Industrial Engineering

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Michael T. Clark
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Accepted by:
Dr. Thomas Sharkey, Committee Chair
Dr. Scott Mason
Dr. Yongjia Song
Sex traffickers often force their victims to work in both commercial sex markets and perform other illicit activities (e.g., drug dealing, theft, and fraud). Current literature has failed to address interdiction models that aim to disrupt all components of a sex traffickers’ operation, including these other illicit activities. In this thesis, we present an interdiction problem, and its single-level linear optimization reformulation, to reduce the profit of a human trafficking network concurrently operating in the commercial sex market and other illicit activity markets. Our novel formulation aims to investigate the practical implications of interdiction decisions made to disrupt a human sex trafficking network operating in several illicit markets. Our work directly models inputs given by our Modeling Effective Network Disruptions (MEND) Advisory Group, whom are domain-level experts in the operations of sex trafficking networks. These suggestions highlight how sex traffickers will force victims to perform other illicit activities in addition to their commercial sex work. Once our interdiction model was created, we investigated several practical disruptions activities that reduced the capacity a victim could work in a targeted market which significantly reduced the profit of the trafficker. Our results show the importance of focusing interdiction activities on disrupting markets in which trafficker could potentially operate, especially market-level disruptions that reduce demand for commercial sex.
DEDICATION

I dedicate this thesis to my mother. She is and always will be my biggest supporter. She has pushed me hard throughout my life to be the best version of myself and to let no obstacle stand in the way of great purpose and achievement. There are no words that would suffice for the gratitude that I have. I would also like to thank the rest of my family who serve as my large army of supporters at every step of the way, this one is for you all.
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Chapter 1

INTRODUCTION

1.1 Defining Human Trafficking

The U.S. Department of State (2020) estimates that there are 24.9 million human trafficking victims worldwide at any given time. The US Department of Homeland Security (2021) defines human trafficking as “the use of force, fraud, or coercion to obtain some type of labor or commercial sex act,” when a sex act is involved this is referred to as sex trafficking. The United States has an ever-growing issue of human trafficking networks plaguing cities across the nation. In this thesis, we will discuss how sex traffickers force their victims to perform various illicit activities and methods in which to disrupt them through an operations research lens.

It’s important initially to identify and define the stakeholders for the purpose of this thesis, many terms used may seem crude or apathetic for such a sensitive issue. Clear and transparent definitions are necessary for the continued discussion of this topic. Further, it is important to acknowledge that we are modeling or abstracting a horrific, traumatic situation. We recognize that our research cannot capture all the complexities of the lived experiences of trafficking victims and survivors.

In this thesis we use the term “trafficker” to describe a third-party who facilitates the commercial sexual exchange using force, fraud, or coercion to recruit, obtain, maintain, induce, transport, or harbor
another person to provide sex to a sex buyer. A trafficker is considered a manager of a trafficking operation, including controlling and directing the commercial sexual activity of their victim(s).

The term “pimp” is used to describe a person who manages and controls the profits of at least one person who trades/sells sex. Pimps may manage one person or more persons involved in commercial sex. A group of people managed by a pimp are sometimes called a “stable.” Pimps often use tactics such as emotional manipulation, physical, or sexual violence to recruit and maintain a person in commercial sex, such as alternately providing or withdrawing love and affection, threats or use of violence, and more. Pimps are characterized as a type of trafficker.

We define a “victim” as someone who is coerced, compelled, manipulated, or forced by a third party to provide commercial sex to a sex buyer. For the purpose of this thesis, there must be a trafficker (i.e. coercive third party) involved as we are looking at operational trafficking networks. In addition, we separately define a “person trading sex” as any person involved in trading through selling their body or any other sexual activity. A person trading sex could do this through a spectrum of circumstances, including coercion and control by a pimp/trafficker, limited choices, or a voluntary choice among options. This includes victims of sex trafficking and sex workers. Our particular focus is on victims of sex trafficking networks and how they may be forced to participate in other illicit activities as part of their trafficking experience.

Human sex trafficking is the fastest growing form organized crime and third-largest criminal enterprise in the world (Walker-Rodriguez and Hill, 2011). Some sex trafficking takes victims from less developed nations like Southeast Asia, former Soviet states, and Central and South America moving them to developed nations in Asia, Western Europe, and North America. Domestically, the United States has many international victims flowing into the country annually, these victims come from those less developed nations and are trafficked into the country. Some even initially come into the country willingly under the pretext of a smuggler but are then sex trafficked throughout the United States, initially being smuggled in
to escape bleak condition in their home country. Additionally, the sex trafficking of US citizens, which we refer to as domestic sex trafficking, is a significant issue. Our particular research is guided by significant domain expertise in domestic sex trafficking.

1.2 Misconceptions

Western cultures often think of human trafficking and sex slavery as young girls being severely abused and treated inhumanely in far corners of the world (Walker-Rodriguez and Hill, 2011). This is common, unfortunate misconception of the problem as these issues plague American cities and towns right under the nose of everyday citizens. For many, the thought of human trafficking and sex slavery as a forced illicit activity in the United States is nearly non-existent. Hollywood film and television show pimps in eccentric, flashy clothing driving over the top vehicles where the adult women they control are voluntarily involved with prostitution without complaint. However, a pimp will traffic their victim against their will by force, threat of force or psychological manipulation. This has become a larger issue than the general populace realizes and the speed at which human sex trafficking is growing is a valid reason for alarm.

Both man-made and natural crises are often considered prime environments for human trafficking but there is little evidence to substantiate this idea (Gozdziak and Walter, 2014). Populations commonly viewed as the most vulnerable are often thought of as those who are trafficked, those thoughts are only exacerbated when a crisis hits that same population. These populations are ones in developing or underdeveloped nations characterized as a far cry from the westernized world. Smuggling and trafficking are often interrelated during crises where those in danger or harsh economic situations may actively seek out smugglers to facilitate migration (Gozdziak and Walter, 2014). After the 2004 tsunami in the Indian Ocean, human trafficking reporting by Western media has increased with every associated crisis but the
accuracy of such reports is questionable. After this crisis, media reported that criminal organizations befriended orphaned children and consequently sold them to sex traffickers. However, as Gozdzia and Walter (2014) note, experts in the field contradict these claims as data shows that there was no increase in verified human trafficking incidents in countries affected by the tsunami.

Even in areas where human trafficking existed before a crisis there is no evidence that a crisis caused an increase in human trafficking cases. After the deadly 2010 earthquake in the island nation of Haiti, there was widespread fear of increased vulnerability of children being trafficked. This is seemingly a reasonable assumption since the trafficking of children existed before the tsunami; however, the trafficking networks have strong ties to international adoption markets (Gozdziak and Walter, 2014). An increase of Western media reports of exaggerated stories of child kidnapping for international adoptions loomed in the shadows of the earthquake.

Gozdziak and Walter (2014) also mention that other disasters have led to very few concerns of human trafficking, showing inconsistencies in assumptions about what populations are most vulnerable to trafficking. After the 2012 nuclear crisis in Japan, there was no widespread fear of trafficking as a result. As noted earlier, Westerners often think of human trafficking as something that exists in far corners of the world and not advanced, Westernized nations.

There are many false archetypes of the typical victim of human sex trafficking. These are commonly thought of as a victim that is kidnapped, uneducated, poor, and/or female (Vijeyarasa, 2015). Both inside and outside of academia often portray a victim as kidnapped, abducted, or sold; however, that is abnormal. The movie ‘Taken’ is a common Hollywood portrayal victims of sex trafficking where a young girl is abducted and forced into the sex trade while being forced to take heavy doses of drugs. Trafficking of abducted victims does take place, but it is representative of the minority. As Vijeyarasa (2015) explains a more common practice is deception, the victims will often know and fully understand the nature of the work but are
deceived by the conditions of the work such as buyers refusing to wear protection and violence from the buyer and trafficker.

It is often assumed that an uneducated person is more likely to be a victim of sex trafficking as it is assumed that education creates increased opportunities for migrants to work in the domestic market and migrate specifically for work (Vijeyarasa, 2015). On the other hand, uneducated individuals are seen as higher risk for trafficking due to the difficulty they may have finding work abroad. Again, these ideas have been dispelled through data showing that the risk of trafficking is higher in those with more years of education (Figure 1).

It was found amongst families in developing nations that the sibling with the most education is most likely to immediately finish school and move to a big city in their home country or abroad, finding work that is hazardous. This is in direct contrast to the commonly held idea of the uneducated being more at risk of being trafficked. This is because when a family significantly invests in the education of one of its

![Figure 1: Relation between education levels and risk of trafficking (Vijeyarasa, 2015)](image-url)
children, it is seen as undesirable for that child to learn the trade or farm works that the rest of the family does so, they are raised without knowing how to perform the trade or farm work. When they graduate, they must move to a place that would allow them to use their education but often have issues finding work and end up working in the sex trade.

Vijeyarasa (2015) goes on to further describe that a widely held assumption is that individuals living in poverty are at an increased risk of being trafficked due to the lack of opportunities in their domestic labor market where trafficking is linked to an exhaustive, desperate search for work abroad. Though it seems logical to assume that a poor person who has a hard time finding work is more likely to become a victim of trafficking, there is no substantial data to support this claim (Vijeyarasa, 2015). There are no widely distributed works that analyze the labor market situation of victims prior to them being trafficked, meaning there is no analysis of whether a victim faced a barrier to entry into their domestic labor market. However, studies do show that victims are often seeking opportunity abroad that will offer more than their available opportunities domestically and are usually not the poorest in their home communities (Vijeyarasa, 2015).

1.3 Sex Trafficking of Americans

As noted by Walker-Rodriguez and Hill (2011) there is an increasing homegrown issue of intrastate and interstate sex trafficking of minors. Unknown to many Americans, there are an estimated 293,000 American minors at risk of being victims of human sex trafficking and commercial sexual exploitation. The idea that these victims are yanked from the street and thrown into a van or lured by a zip tie or another related object on a vehicle are common misconceptions that often go viral. Stealing young women and girls from the street would create unwanted attention and unwanted risk for a trafficker, especially when there are many alternative methods of acquiring victims without the buzz surrounding it.
A majority of the homegrown sex trafficking victims are runaway or thrown-away youths who already live on the streets and become victims of sex trafficking under the false pretext of safety, coming from abusive households and families who have abandoned them (Walker-Rodriguez and Hill, 2011). Eventually, they involve themselves with prostitution to financially support themselves and acquire things that they need or want (e.g., housing, food, drugs). This is a harsh reality of what goes on in many towns and cities across the United States. Youths tend to have a soft spot in the hearts of adults, the idea that minors grow up in such difficult circumstances is often unimaginable, especially in the U.S. where it is often seen as the most idyllic of the Western world.

As shown by the characterizations, human sex trafficking is not a one size fits all issue that can be applied to a standard population of individuals. This crisis affects all walks of life in all areas of the world. We have worked to dispel the idea that only young girls from underdeveloped nations are trafficked with the intent of showing that sex trafficking also happens in the back yards of everyday Americans, often unknowingly. Victims come from every race and gender. Through our work we hope to assist in curbing this crisis through a unique novel modeling approach that focuses on how victims of sex trafficking may be forced to perform other illicit activities.

1.4 Problem Motivation

Current research on sex trafficking networks has not yet captured how traffickers may force their victims to perform other illicit activities, such as selling drugs or shoplifting. We present a novel model with two specific aims. The first aims to address how traffickers force victims into various illicit markets through a quantitative network operations model. The proposed model was formulated with a single trafficker controlling multiple victims’ activities within multiple illicit activity markets, although it could be extended easily to consider multiple traffickers forcing their own set of victims into the various illicit markets.
The second aims to quantitatively observe how traffickers move their victims through sex trafficking and other illicit activity markets when faced with interdictions and disruptions. After verifying a preliminary functioning model, an interdiction element was added and further verified through collaborations with a domain expert.

We present an interdiction model where an attacker seeks to disrupt a human trafficking network that forces its victims to perform a variety of illicit activities, including selling sex, selling drugs, and fraud. The trafficking network is modeled through insights obtained by qualitative research, including stakeholder interviews. The model helps to understand how interventions into sex trafficking can cause the prevalence of other illicit activities to rise, which would be a natural response for traffickers in ensuring their revenue stream stays consistent after these interventions.

To meet our modeling goals, we had to initially determine and understand what illicit activity markets a trafficker may force their victims to enter and how the trafficker decides which markets are best to operate their trafficking enterprise.

![Figure 2: Trafficking Network](image)
Figure 2 features a single trafficker with control over several victims. Those victims are then forced to operate in various illicit markets. Capacity limits are represented through hours. A victim has a limited number of hours that they can be controlled by the trafficker. A victim can only work a limited number of hours in each market. There is also only a limited number of overall hours that can be worked by all victims in the market. There is an associated revenue per hour that individual victims can make in each market. For example, Victim A may make $40/hour in the illicit drug market while Victim B may make $55/hour doing the same task based on previous experiences in the drug market. From the trafficking perspective, the model is built to optimize the total revenue for the trafficker, since traffickers tend to be motivated by profits.

Furthermore, the interdiction model is built in such a way that it focuses on best disrupting activities of the trafficker, i.e., it seeks to minimize the maximum revenue the trafficker can obtain. Disruptions can either remove an individual victim from the network or perform an activity to disrupt the demand across certain markets. These disruptions are implemented to decrease a market activity by some fixed percentage. For example, Disruption Activity X may reduce the overall hours of Market A and B by 20%; however, it reduces Market C by 0%. Furthermore, each disruption requires a certain number of resources; the interdiction problem seeks to best disrupt the operations of the network within a limited resource budget.

The remainder of this thesis is organized as follows. Chapter 2 presents an overview of the relevant literature in both human trafficking and interdiction models to disrupt illicit trafficking networks. Chapter 3 presents the mathematical models used to measure the effect of disruption activities. Chapter 4 presents the data collection methods and results of the model. Chapter 5 concludes this thesis.
Chapter 2

LITERATURE REVIEW

2.1 Background on Understanding Sex Trafficking Networks

Research on sex trafficking networks has proved difficult given its hidden, illegal, highly stigmatized, and often dangerous nature (Martin et al., 2017). Martin et al. (2014) highlights both the difficulty and bias of research on sex trafficking networks. They go on to express that sex trafficking and commercial sexual exploitation is a market built on exploitation, violence, and brutality structured around supply and demand like a business. The demographic of victims includes children, women, men, and transgender people (Martin et al., 2017). Women and girls with vulnerabilities are the general targets of a traffickers: being runaway and/or homeless, living in poverty and/or unable to meet basic needs, experiencing cognitive delay or mental health issues, using drugs or alcohol, and/or absence of social protections against exploitation (Martin et al. 2014). As explained by Martin et al. (2014), once in the network, traffickers will assign victims to a particular business model: brothel/brothel-like arrangements, escort services, street-based work, and closed sex buyer networks.

A potential important disruption mechanism to sex trafficking is to focus on reducing demand for commercial sex, i.e., disrupting the demand-side of the network. There is no practical method to generate a representative sample of those who purchase sex (Martin et al., 2017). A Minnesota study concluded that sex buyers are predominantly middle-aged, white, married men with vast occupational backgrounds (Martin et al. 2017). A 2014 study found that “about 14% of men in the United States report having ever
paid for sex, and only 1% report having done so during the previous year” (Monto & Milrod, 2014). Sex buyers originate from the internet, direct in-person solicitation, and word-of-mouth networks, which often will conceal the trafficking aspect of the commercial sex buying market (Martin et al. 2017). Research shows that sex buyers mainly seek a quick and anonymous sexual experience without an emotional connection (Martin et al., 2017).

In addition to understanding the profile of sex buyers, it is important to understand the profiles and decision-making of other participants in the sex trafficking network. Dank et al. (2014) provides comprehensive profiles of common stakeholders in sex trafficking networks across the United States. Their study gives insight into who traffics, buys, and supplies sexual encounters as the scope and profit vary by geographic location. The work of Dank et al. (2014) provides an important source of data for this thesis.

2.2 Mathematical Modeling of Disrupting Sex Trafficking Networks

Historically, network interdiction has been used to model nuclear and drug trafficking networks. Morton et al. (2007) examines interdiction models to disrupt the ability for nuclear materials to be smuggled across borders. Wood (1993) used network interdiction to quantitatively study methods to reduce the flow of drugs and precursor chemicals moving through drug trafficking networks South America. His model successfully minimized the maximum flow of product through the network using an interdictor to interdict network arcs with limited resources. The success of these papers proved it possible to apply network interdiction to real-world societal challenges.

Drug trafficking network interdiction models continued to be formulated and implemented, expanding in scope and depth. Malaviya et al. (2012) formulated a network interdiction model focused on scheduling the interdiction activities of law enforcement in illegal drug supply chains. The final analysis provided direction to law enforcement for effective policies to implement in their interdiction activities. In
a subsequent study, which also scheduled interdiction activities to minimize the max flow, Enayaty-Ahangar et al. (2018) formulated a large-scale optimization approach for solving an application of a multi-period bilevel network interdiction problem. Further studies dove into layered drug trafficking networks where network interdictions on an information flow network, using a novel multi-step dual-based reformulation technique, had profound negative affect on the physical flow network (Baycik et al., 2018). The physical flow network, both practically and mathematically, is only operational if the information flow network receives enough demand. Other researchers developed a spatially explicit agent-based-model which found that a trafficker’s resilience to interdictions are partly due to natural consequences of the interdiction itself and this result supported by qualitative findings (Magliocca et al., 2019). Furthermore, Shen et al. (2021) built a bi-level integer programming model with formulated interdictions capturing the interdependencies of transnational criminal organizations.

With the early success of Wood (1993), other OR researchers found it possible to model human trafficking networks through traditional network formulations. These have proved to be powerful analytical tools used to understand and disrupt these operations. As noted by Sharkey et al. (2021), industrial and systems engineering applications have proved successful in helping address the issue of human trafficking, especially when done in collaboration with domain experts: network interdiction models can capture the full scope of sex trafficking networks and subsequently disrupt them (Kosmas et al., 2020), location models can output optimal locations to emplace shelters that support survivors, and data analytics tools can be implemented for insight into trends of commercial sex advertising (Coxen et al., 2021) and illicit massage parlors (White et al., 2021). These applications can only be deemed credible if they acknowledge potential unintended consequences and have the favor and support of domain experts. Kosmas et al. (2022) highlight the importance of transdisciplinary research to conduct appropriate research related to human trafficking networks as it seeks to address complex societal challenges through the integration of knowledge and methods of different disciplines. Domain experts should be consulted to obtain appropriate and
accurate data. They make it possible to appropriately apply network interdiction modeling of sex trafficking networks.

Researchers have found it difficult to obtain reliable data on human sex trafficking operations due to the detection prevention measures that trafficker’s employ. Recent works have formulated network generators of sex trafficking network, outputting the relationships between traffickers and victims; and, subsequently verified by a multitude of domain experts. (Kosmas et al., 2022). The network generator enables OR researchers to access realistic sex trafficking networks and further introduces flow as novel term used to conceptualize the ability of a traffickers to control their victims. Further research used a more conventional network interdiction approach to interdict a modeled sex trafficking network (Kosmas et al., 2020). This application interdicted arcs of the network but allowed the trafficker to introduce new arcs after an interdiction decision was made, resulting in a trafficker being only slightly disrupted since replacing victims was unchallenging.

Current research proves that it is both feasible and realistic to apply interdiction modeling to sex trafficking networks and its importance to understanding how a sex trafficker reacts to disruptions in their network; but one must be thoughtful in both the creation of the data and the construction of the model. This thesis uses that approach in formulating the research question, which is motivated by a survivor-centered advisory group and their inputs into larger research projects. Subsequently, the assumptions in the data are verified with a domain expert. Present research does not exhaustively address how sex traffickers control the flow of their victims into other illicit markets with and without network interdictions. Our research aims to answer the practical implications of interdiction decisions made to disrupt a single sex trafficker network that additionally operates in other illicit markets.
Chapter 3

MODELING

3.1 Problem Statement and Assumptions

In this work, we present two network optimization models representing a single human sex trafficking network – one that focuses on optimizing the operations of the trafficker(s) and one that focuses on best disrupting these operations. The trafficker(s) control victims and force them to perform activities within different illicit markets. Each victim has a capacity limit in hours per week, capping the number of hours a victim can work per week. Each market has an individual demand capacity that cannot be exceeded when summing the number of hours that the victims in the network work in that market. In both models, the goal of the trafficker is to maximize profit. However, the interdiction model is formulated to minimize the trafficker’s profit. It will be more difficult for the trafficker since there are methods employed to hinder the trafficker from accessing the various markets at their initial levels or decreasing the number of victims under their control, thus reducing their profit. Overall, we look to understand what interdiction decisions are executed by the model to minimize a traffickers’ profit and how a trafficker will move their victims through the markets to maximize profits, especially in response to interdictions.
Our assumption for victim and market capacity is that it can be best expressed in terms of hours. By using time constraints, it's more realistic in the context of this problem. Though a trafficker can want a victim to work 24 hours a day, 7 days a week, that is not a realistic environment in which the victim can operate. The victims will work more than an average person who works a traditional work schedule but many of these markets mainly operate in the evening and through the night. It could be a waste of resources for the trafficker to force the victim to work midday. In addition to the market capacity in hours, the markets will have a fixed revenue per hour associated with individual markets.

We assume that a trafficker will have an equivalent initial control capacity amongst all its victims. This is to maintain that, for our research, a trafficker has full control over all the victims and control is not shared between another trafficker in our research, though we acknowledge that this is not always the case in the real-world settings. This assumption helps to scope our initial modeling efforts and focus on the main contribution of examining trafficking networks that force their victims to participate in multiple illicit markets.

Interdiction activities are executed to disrupt one or more markets or to remove victims from the network. The disruptions aimed to reduce the profit a trafficker can make in a market. However, we assume and subsequently model that a disruption will directly affect the market capacities rather than the revenue per hour of a market.

### 3.2 Model Formulation

The following is a detailed description of the notation we are using to formulate the network optimization model. In Section 3.2.1, we describe the initial network formulation, and in Section 3.2.2, we describe the interdiction problem. We begin by discussing the sets, parameters, and decision variables.
Sets:

- $M$: Set of markets, $m$
- $V$: Set of victims, $j$
- $A$: Set of disruption activities, $i$
- $T$: Set of traffickers, $t$

Parameters:

- $r_{mj}$: Revenue generated in each market $m$ by victim $j$ ($$/hour$)
- $ub_{tj}$: Capacity of trafficker $t$ to control victim $j$ (hours)
- $C_m$: Market capacity (hours)
- $U_{jm}$: Capacity of victim $j$ to work in market $m$ (hours)
- $VB_j$: Budget to remove victim $j$
- $a_i$: Budget required to implement market-level disruption activity $i$
- $P_{im}$: Percent of market ‘$m$’ disrupted by activity $i$
- $C$: Big-M value ($C = 1000$)
- $b$: Budget of disruptions activities

Interdiction Decision Variables:

- $Z_i$: Binary variable. 1 if disruption activity $i$ is implemented
- $z_j$: Binary variable if victim $j$ is removed from the network

Initial Network Decision Variables:

- $y_{tj}$: Flow from trafficker $t$ to victim $j$
- $x_{jm}$: Flow from victim $j$ to market $m$

Dual Network Decision Variables:

- $\pi_j$: Dual variable of victim $j$ flow balance constraint
- $\pi_m$: Dual variable of market $m$ capacity constraint
- $\theta_{jm}$: Dual variable of the capacity constraint of flow from victim $j$ to market $m$
- $\theta_{tj}$: Dual variable of the capacity constraint of flow from trafficker $t$ to victim $j$
- $\alpha_{im}$: Linearization variable of the product of market level interdiction $i$ and the dual variable associated with the capacity constraint of market $m$
- $\beta_{tj}$: Linearization variable of the product of victim interdiction $j$ and the dual variable associated with the flow capacity constraint between trafficker $t$ and victim $j$
3.2.1 Formulation of Traffickers Operations

We now present a formulation that models the trafficker’s profit-maximizing behavior, subject to constraints on the number of hours victims can work and the capacity of the markets.

\[
\text{Max } \sum_{j \in V} \sum_{m \in M} r_{mj}x_{jm} \tag{3.1a}
\]

Subject to:

\[
y_{tj} \leq ub_{tj}, j \in V, t \in T \tag{3.1b}
\]

\[
\sum_{j \in V} x_{jm} \leq C_m, m \in M \tag{3.1c}
\]

\[
\sum_{t \in T} y_{tj} - \sum_{m \in M} x_{jm} = 0, j \in V \tag{3.1d}
\]

\[
x_{jm} \leq U_{jm}, j \in V, m \in M \tag{3.1e}
\]

\[
y_{tj}, x_{jm} \geq 0 \text{ for } t \in T, j \in V, m \in M \tag{3.1f}
\]

3.2.1.1 Initial Model Formulation Explanation

Equation (3.1a) represents the objective of the initial model formulation. The objective maximizes the sum of the products of the revenue generated of a fixed victim by the number of hours a victim works a fixed market. Constraints (3.1b) means that a trafficker cannot force a victim to work more hours than the upper bound control capacity limit. Constraints (3.1c) ensures the sum of hours the victims in a network work a market does not exceed the market’s capacity. For example, if a network has two victims that individually have the capacity to work market A for 10 hours, but the market capacity is 15 hours then one
victim can work their full 10 hours in the market, but the other victim can only work 5 hours in that same market. Constraints (3.1d) reaffirms that the total number of hours a trafficker controls an individual victim is equal to the total number of hours that individual victim will work the markets. Constraints (3.1e) ensures that an individual victim does not work a particular market more than their capacity limits of that market. Constraints (3.1f) represents the non-negativity constraint for the variables.

3.2.2 An Interdiction Problem to Disrupt the Trafficking Operations

We now consider an interdiction problem to disrupt the trafficking operations by removing victims from the network which then impacts the right-hand side of Constraints (3.2b) and implementing market-level disruption activities that reduce market capacity by impacting the right-hand side of Constraints (3.2c). We first define the set of feasible interdiction decisions as $Z$. For our modeling purposes, we have that $\Gamma = \{(Z, z): \sum_{i \in A} a_i Z_i + \sum_{j \in V} V B_j z_j \leq b, \ Z_i \in \{0, 1\} \ \forall i \in A, z_j \in \{0, 1\} \ \forall j \in V\}$. The initial interdiction formulation is:

$$\begin{align*}
\text{Min}_{(Z, z) \in \Gamma} & \sum_{j \in V} \sum_{m \in M} r_{mj} x_{jm} \\
\text{Subject to:} & \\
& y_{tj} \leq ub_{tj} (1 - z_j), j \in V, t \in T \quad (3.2b) \\
& \sum_{j \in V} x_{jm} \leq c_m \left(1 - \sum_{i \in A} \sum_{j \in V} P_{im} Z_i \right), m \in M \quad (3.2c) \\
& \sum_{t \in T} y_{tj} - \sum_{m \in M} x_{jm} = 0, j \in V \quad (3.2d) \\
& x_{jm} \leq u_{jm}, j \in V, m \in M \quad (3.2e) \\
& y_{tj}, x_{jm} \geq 0, t \in T, j \in V, m \in M \quad (3.2f)
\end{align*}$$
3.2.3 Single-Level Linear Optimization Formulation of the Interdiction Problem

We now present the single-level linear optimization formulation of the interdiction problem presented in Section 3.2.2. In particular, for a fixed set of interdiction decisions, the trafficker’s problem becomes a linear program. Therefore, we can take the dual of the linear programming formulation and then apply a standard linearization technique to the product of the dual variable and the interdiction variables. The single-level formulation is:

\[
\text{Min } \sum_{m \in M} \left( \pi_m C_m - \sum_{i \in A} C_m P_{im} \alpha_{im} \right) + \sum_{t \in T} \sum_{j \in V} (\theta_{tj} u_{tj} - \beta_{tj} u_{tj}) + \sum_{j \in V, m \in M} \theta_{jm} U_{jm} \tag{3.3a}
\]

Subject to:

\[
\sum_{i \in A} a_i \cdot Z_i + \sum_{j \in V} V_{Bj} \cdot z_j \leq b \tag{3.3b}
\]

\[
\pi_j + \theta_{tj} \geq 0, t \in T, j \in V \tag{3.3c}
\]

\[
-\pi_j + \pi_m + \theta_{jm} \geq r_{m,j}, t \in T, j \in V, m \in M \tag{3.3d}
\]

\[
\alpha_{im} \geq \pi_m - (1 - Z_i)C, m \in M, i \in A \tag{3.3e}
\]

\[
\alpha_{im} \leq \pi_m, m \in M, i \in A \tag{3.3f}
\]

\[
\alpha_{im} \leq \pi_m, m \in M, i \in A \tag{3.3g}
\]

\[
\beta_{tj} \geq \theta_{tj} - (1 - z_j)C, t \in T, j \in V \tag{3.3h}
\]

\[
\beta_{tj} \leq C \cdot z_j, t \in T, j \in V \tag{3.3i}
\]

\[
\beta_{tj} \leq \theta_{tj}, t \in T, j \in V \tag{3.3j}
\]

\[
\pi_j \text{ is free, } j \in V \tag{3.3k}
\]

\[
\pi_m, \theta_{jm}, \theta_{tj}, \alpha_{im}, \beta_{tj} \geq 0, m \in M, j \in V, t \in T, i \in A \tag{3.3l}
\]

\[
Z_i, z_j \in \{0,1\}, i \in A, j \in V \tag{3.3m}
\]
3.2.3.1 *Explanation of the Single-Level Linear Optimization Formulation of the Interdiction Problem*

The single level linear optimization formulation of the interdiction problem is reformulated from the min-max structure using linear programming duality and linearization techniques. Equation (3.3a) represents the objective function of the dual of the inner problem (i.e., the problem faced by the trafficker once the interdiction decisions are fixed) where we have linearized the products of the interdiction decisions and the appropriate dual variables.

Constraints (3.3b) ensures that the sum of the budget’s used for removing victims from a network and executing disruption activities does not exceed the overall allotted budget for performing these actions. Constraints (3.3c) are the dual constraint associated with the flow variable, $y_{ij}$. Constraints (3.3d) are the dual constraint associated with flow from a victim to a market, $x_{im}$.

Constraints (3.3e)-(3.3g) are the linearization constraints for the product of $Z_i$ and $\pi_m$. Note that if $Z_i$ is equal to 0, these Constraints (3.3f) force $\alpha_{im}$ to be zero as well. If $Z_i$ is equal to 1, Constraints (3.3e) and (3.3g) imply that $\alpha_{im}$ is equal to $\pi_m$. Constraints (3.23)-(3.3j) are the linearization constraints of $z_j$ and $\theta_{ij}$ and have similar implications as the linearization constraints previously discussed when $z_j$ is equal to 0 or to 1.

Constraints (3.3k) allows the dual of victims to take on any value. Constraints (3.3l) represents the non-negativity constraint for the variables. Lastly, constraints (3.3m) affirms the binary condition of the interdiction variables. This single-level reformulation will be how we solve the problem for various interdiction budget levels.
Chapter 4

EXPERIMENTAL DESIGN

4.1 Data Collection and Justification

After formulating the model, we worked to collect data that would be appropriate for the formulation. Data was collected through research in academic sources, studying government websites, and discussions with a domain expert.

Our goal was to model how traffickers move victims through various illicit markets when the sex selling market is constrained. We immediately determined that we would use the markets of commercial sex, shoplifting, check boosting, and drugs. Through initial research, we found that these were common illicit activities the sex traffickers forced upon their victims (MEND Advisory Group, 2021). After some initial research on the operations of these markets, we presented the model formulation and initial data to a domain expert for verification.

Our model looks at five markets: high-end commercial sex selling, low-end commercial sex selling, theft, drugs, and fraud. In this research we describe the high-end market as a sex selling market in which victims can make a greater profit per hour for the trafficker due to the nature of the work. A high-end market is one that buyers are willing to pay more per hour for like an escort or brothel. In this model, we define the high-end market as a brothel. A low-end market, in this thesis, is describe as a sex selling market
in which victims make much less per hour for the trafficking performing this type of work. For our research, the low-end market is considered sex selling on the street (street prostitution). We assume that, in a trafficking network, if a trafficker controls victims in both the high-end and low-end markets, the victims will only work in one market or the other. In other words, a victim that does any work in the high-end market will not do any work in the low-end market and vice-versa. This is because victims in the high-end market are considered more desirable to buyers and are typically possess attributes that attract a different type a client. A trafficker would not want to a victim that can make money in the high-end market to work the low-end street market. For the purposes of this research, we call a victim that works in the high-end market a 'high-end victim' (HE), and a victim that works in the low-end market a 'low-end victim' (LE). Additionally, we assume that the capacity HE victim to work in the high-end market will be greater than the capacity of a LE victim to work in the low-end market. This is because the work in the low-end market is tougher and more taxing than the work in the high-end market. Additionally, since a HE victim is more valuable to the trafficker, they would not want to overwork that victim and thus reduce their profits in the long run.

We describe the theft market as one where a victim is forced to shoplift products from a store and resell them on the street. This practice is known as ‘boosting.’ The trafficker will force a victim to do this as an alternative method to selling sex, their main source of profit. This is done when the sex selling market is either constrained by demand capacity or disrupted due to some disruption activity that reduces the ability for the trafficker to make money.

The fraud market is described as one where the individual victims are forced to commit government benefits fraud. Since benefits are reoccurring per month this is a stable profit for the trafficker though relatively low when all others are considered. Due to the high consequences associated with defrauding the government, traffickers force their victims to do this at the risk that their victim will be caught and removed from their network.
The drug market is described as one where the individual victims sell drugs on the street. Many of the victims and buyers of the low-end sex market are drug addicted so the two markets are often closely related. For this research, we do assume a specific type of drug that the victims are selling for the trafficker, but common drugs would be meth, heroine, and crack cocaine.

Our model looks at how a human sex trafficker will force their victims into other illicit activities, so we assume that the demand and capacity limits will be greater in the markets of selling sex since that is what the trafficker is most familiar with. In the trafficking networks that we are modeling, the trafficker will have greater access to sex selling markets since they will likely have established buyers, an area they know well, and a fine understanding of the interworking’s of selling sex.

We assume that the drug market will have the next highest capacity since drugs are closely related to the sex-selling markets. Often, traffickers are also drug dealers themselves so it would make sense for the traffickers to force their victims to sell drugs for them. Being that these are street drugs, we assume and verify through data that the profits will be like those made in the low-end sex selling markets.

We assume that theft and fraud will have the lowest capacities. For theft, the return on investment will not be worth allocating a lot of resources toward it from the perspective of the trafficker. When they force their victims to steal a product it may take several hours of more work to resell those items on the street, effort that can be put toward working in other markets that see immediate returns. For fraud, since it all comes from benefits fraud there is only so much a victim can do per week which will mainly be maintenance activities. Maintenance activities will be checking to ensure that the benefits are coming in properly and that there a no delays.

Furthermore, we assume that the market capacities of the low-end and high-end markets will be based on a formula accounting for the number of LE and HE victims a trafficker controls and the capacity of the type of victim. This done to appropriately balance a network. If a trafficker has far more LE victims than
HE victims, it would not make sense for there to be a large demand for the high-end market in that particular network, and vice-versa.

During and after the discussion it was decided that the final markets would be low-end sex, high-end sex, drugs, theft, and fraud. From the discussion, we gathered that it was more common for a trafficker to delineate victims that would work in the high-end and low-end markets has the victims of those served different purposes. We agreed that though the victims would work in either high-end markets or low-end markets it was appropriate to model that they would all potentially work in the drugs, theft, and fraud markets.

It was further determined the theft was a more appropriate, encompassing term than shoplifting. This is because shoplifting is a term that generally specifies retail theft, while theft can be used to describe any all any taking of items that don’t belong to the victim (i.e., shoplifting, petty theft, etc.). A trafficker does not care where the items come from as long as the items can be resold for a profit. The traffickers would be content with the victim stealing money or valuables from their buyers of commercial sex.

The market fraud was chosen over check boosting for a few reasons. Check boosting is difficult to quantify in revenue per hour since a victim can write a check for various amounts. It was also determined that benefits fraud was a more common method than check boosting, as many victims are forced to collect benefits, fraudulently. We realized that data on benefits fraud was more readily available and is more justifiable as data source than check boosting since it is a well-known illicit activity of sex trafficking victims.

4.1.1 Commercial Sex Victims

The number of victims was initially decided to be varied from 2-6 victims for a single trafficker network. However, once the group decided to split the commercial sex market into two, we decided to fix the number of victims but vary the type of victims that each trafficker would have totaling six networks. The six networks and types of victims are shown in Table 1.
By having a varied number of types of victims yet a set number of victims, we can better analyze both the model and its outputs. We hypothesize that the more high-end victims a trafficker has the more profit a trafficker will make because a high-end victim is worth more to the trafficker and can generate more revenue per hour in the high-end market than a low-end victim can generate in the low-end market.

4.1.2 Stakeholder Profiles

Our initial plan was to utilize one set of values for the revenue of high-end and low-end commercial sex markets; however, Dank et al. (2014) concluded that potential revenue from commercial sex trafficking varies extensively by city. Dank et al. (2014) estimates the size and structure of the commercial sex market in eight major U.S. cities. Each city has different venues for commercial sex trafficking with varying trafficker, victim, and buyer profiles. Some examples of venues studied are street, internet, brothels, erotic massage parlors, topless bars, and escort services. Not all cities had data for each venue. In this study, we used the data for brothels to quantify the high-end commercial sex market and street sex selling to quantify the low-end commercial sex market.

After comparing the data of the cities, we narrowed down our focus to three of the cities analyzed by Dank et al. (2014): Atlanta, Miami, and Seattle. These cities had diverse trafficker, victim, and buyer profiles and had overlapping information for the commercial sex venue (Table 2).
The diversity of the participants, as shown by Table 2, is an important aspect of the research as it gives us insight into how much revenue can be made among traffickers in each city. Brothels in Atlanta and Miami are generally controlled by Latino’s, while brothels in Seattle are controlled by Vietnamese nationals. Furthermore, the victims of brothels differ by city. In Atlanta and Miami where brothels are controlled by Latino traffickers the victims are smuggled Mexican women and Latina women, respectively. In Seattle where Vietnamese nationals control the brothels, the victims are Vietnamese women whose citizenship status range from illegal, refugees, and on asylum.

In the low-end street market, men of all races/ethnicities are buyers of commercial sex. The victim profile in Miami and Seattle are typically drug addicted women, while in Atlanta victims are women along
with some men and boys. Note that Dank et al. (2014) does not give data for the trafficker’s profile in the street commercial sex market in Miami.

It’s important to discuss the discrepancy between the given data and our model, where our model is formulated for a single trafficker controlling both the high-end and low-end victims in each city. As shown by Table 2 the trafficker profiles differ for each venue in a city, so in a real-life scenario the data we use would not be accurate. Research shows that a trafficker will often control both high-end and low-end victims; however, data on the revenue generated in those markets is scarce. Dank et al. (2014) offered the best data as their research and data collection methods were both extensive and accurate and had the support of our domain expert. This allowed us to confidently utilize and combine their data until further qualitative studies are performed to collect revenue data amongst single trafficker networks.

### 4.1.3 Market Revenue

Table 3 shows the revenue of the commercial sex market by city. As shown, Atlanta and Seattle have the most lucrative high-end commercial sex markets at $200/hr, while Miami has the potential of making only $100/hr. Of the low-end commercial sex market, traffickers in Atlanta can generate the most revenue at $100/hr while traffickers in Seattle and Miami can only generate $65/hr and $45/hr, respectively. These values are used in our formulation as the revenue that each victim can generate for

<table>
<thead>
<tr>
<th>Commercial Sex Market</th>
<th>City</th>
<th>Revenue ($/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-end</td>
<td>Atlanta</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>Miami</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Seattle</td>
<td>200</td>
</tr>
<tr>
<td>Low-End</td>
<td>Atlanta</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Miami</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Seattle</td>
<td>65</td>
</tr>
</tbody>
</table>

Table 3: Revenue of Commercial Sex Market ($r_{m,j}$)
their trafficker when working in the commercial sex market. This data is based on results of Dank et al. (2014).

The other illicit markets will generate around the same revenue per hour (if not less) than the low-end commercial sex market. These other markets are methods for the trafficker to both generate additional revenue and supplement revenue when capacity as been reached in the commercial sex markets or when a market has been interdicted. For the drug market, we researched general data on drug dealers and the revenue they generate. Since selling drugs is a market tapped by many external to the sex trafficking networks it a competitive market for all. The revenue that victims will generate per hour for the traffickers selling drugs will be equivalent to the revenue generated by all drug dealers. Buyers will simply want the cheapest product so anyone selling drugs, both victims and non-victims, will have to offer competitive rates. MacCoun and Reuter (1992) found that a street level drug dealer can earn around $20/hour selling drugs. When adjusted for inflation a dealer can earn $25/hour (Table 4). We used this value for the drug market in our model, aligning with the research supporting selling drugs and sex trafficking victims. The drug market is typically associated with the low-end sex market. A victim will sell drugs on the street like how they will sell sex on the street. Selling drugs is characterized as a low-end activity both internally and externally to trafficking networks so it is appropriate to use this value which is lower than the revenue generated from all three low-end sex markets in our cities studied.

<table>
<thead>
<tr>
<th>Illicit Market</th>
<th>Revenue ($/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drugs</td>
<td>25</td>
</tr>
<tr>
<td>Fraud</td>
<td>56.67</td>
</tr>
<tr>
<td>Theft</td>
<td>50</td>
</tr>
</tbody>
</table>

Table 4: Revenue of other Illicit Markets ($_{m,j}$)
As noted by the domain expert, fraud amongst victims of sex trafficking is usually in the form of benefits fraud. We researched the most common form of government benefits fraud and found that Supplemental Security Income (SSI), Social Security Disability Insurance (SSDI), and Supplemental Nutrition Assistance Program (SNAP) were the most common programs to be defrauded. SSI and SSDI are forms of disability assistance, people will fake a disability/injury to receive these benefits every month. SNAP, commonly referred to as Food Stamps, is to poor individuals and families afford groceries each month. People will commit fraud by falsifying the number of people in their household which gives you more money per month and/or by selling their foods stamps for cash since they can only be used for food. On average a person will receive $794/month in SSI and $1222.75/month in SSDI (Bauer, 2022). Additionally, in fiscal year 2022 a single person on SNAP will receive $250/month from the federal government and may receive additional assistance from the state in which they reside; however, that is unaccounted for in our data (CBPP, 2022). We summed the three values and divided by the number of hours that a victim in our model can dedicate to fraud and determined that a victim will make $56.67/hour working in the fraud market (Table 4). Like the drug market, benefits fraud is a universal activity that is not exclusive to victims of sex trafficking. It is more than realistic to use data that can be applied to any person committing benefits fraud. We summed the benefits of SSI, SNAP, SSDI because not only is it common for a fraudster to commit multiple types of fraud, but a trafficker will likely force their victims to do this as well since the goal is to generate the most revenue. It is without doubt to say that while there is a small minority of those receiving benefits that are doing so fraudulently, an overwhelming majority of those receiving benefits are doing so out of legitimate need.

Theft is the most difficult market to quantify exacerbated by our broad definition of the theft market. Since theft is a way for traffickers to supplement income, we concurred that its revenue should be similar to the revenue generated by both the other illicit markets and the low-end commercial market. A victim will spend more time acquiring items than selling them, so that had to be accounted for. These goods range from designer items to petty theft from a local store or unlocked vehicle. A victim must then turn the
goods for a profit. We decided on a revenue of $50/hour and verified if this value was realistic with our domain expert.

4.1.4 Victim Capacity

In our formulation, we modeled that a single trafficker has a limited number of hours per week that they can control their victims. Research shows that a victim will be forced to work more than a traditional 40 hours/week job; however, the trafficker will not want to overwork its victims, hindering their profits in the long run, as these illicit markets are intensive and draining. The trafficker-victim capacity ($u_{b_{ij}}$) of this model is 50 hours/week, which appropriately shows that a victim is worked more than standard employment yet not overworked. Additionally, being that our modeled trafficker will control five victims, the trafficker must be able to appropriately command and control all of them significantly affecting capacity limits as number of victims and control capacity limits work as in inverse relationship.

Victims will be limited to the number of hours they can individually work in each market per week, $U_{jm}$ (Table 5). We consulted the domain expert to better understand what victims will typically do each week. It was concluded that victims will put the least amount of effort towards fraud and theft. After setting up and receiving the benefits each month, victims will perform maintenance activities to ensure that the benefits will continue being paid out each month and/or looking into alternative benefits that they can receive, thus working in the fraud market for a maximum of 10 hours/week. Additionally, work in the theft market will be low as there is little return on investment and it is a high-risk activity with mid-level reward. As noted in our assumptions, the return on investment will not be worth allocating a lot of resources toward it from the perspective of the trafficker. When they force their victims to steal a product it may take several hours of more work to resell those items on the street, effort that can be put toward working in other markets that see immediate returns; but theft is a method used to supplement revenue in authentic sex trafficking networks. Thus, an individual victim can work in the theft market for 10 hours/week.
<table>
<thead>
<tr>
<th>Market</th>
<th>Capacity (hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-End</td>
<td>40</td>
</tr>
<tr>
<td>Low-End</td>
<td>30</td>
</tr>
<tr>
<td>Theft</td>
<td>10</td>
</tr>
<tr>
<td>Drugs</td>
<td>25</td>
</tr>
<tr>
<td>Fraud</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 5: Capacity of Victims in Markets ($U_{jm}$)

The commercial sex market is the primary role of the trafficker and victims so capacity limits will be greater in those markets. High-end victims traditionally have an easier work-life when compared to low-end victims due to the nature of their work in brothels and as escorts with clients willing to pay more for their services. In this study, a high-end victim will have the capacity to work in the high-end commercial sex market for 40 hours/week. Low-end victims, who have a more difficult work-life when compared to high-end victims, will have a capacity limit of 30 hours/week.

Research shows the close relationship of the drug market with the low-end commercial sex market. Thus, the capacity limits of victims in the drug market will be like the victim capacity limits in the low-end market. At 25 hours/week this capacity appropriately imitates how closely intertwined the two markets are. In a traditional sex trafficking network, the low-end victims will generally be forced to sell drugs at a greater rate than high-end victims, but we know that all victims are generally forced to do so at various levels so it is appropriate to assume in our formulation that all victims will have the same capacity limit in the drug market.

4.1.5 Market Capacity

The presented model accounts for overall capacity limits of the markets ($C_m$). This is necessary as all markets cannot realistically manage being worked to the summed capacity limits of the victims, while other markets can operate under those summed capacities. We concluded that theft and fraud can operate at the summed capacity limits of the victims and was set at 50 hours/week. Theft, in all forms, is something
that will not realistically have a capacity limit. Benefits fraud can be executed by anyone and will also not realistically have a limit, current research does not suggest any increased governmental efforts to limit this outside what is already being done.

The capacity of commercial sex markets should not be limited as that is the primary market in which the modeled single trafficker network operates. The capacity limits should be greater than the sum of the victim’s capacities. Equations (4.1a) and (4.1b) set capacities greater than required for the sum of the victims that operate in those markets.

\[
Low - end \ market \ capacity = 1.1 \cdot \sum_{m \in M} U_{j,low - market} \cdot number \ of \ low - end \ victims \quad (4.1a)
\]

\[
High - end \ market \ capacity = 1.1 \cdot \sum_{m \in M} U_{j,high-end \ market} \cdot number \ of \ high - end \ victims \quad (4.1b)
\]

This expanded capacity is imperative to the model as the commercial sex trafficking market is one that the trafficker will know best and be able to navigate more freely (without disruption activities).

### 4.1.6 Disruption Activities

What separates our model from previous literature are the market-level disruptions. Disruptions are modeled to affect the capacity limits of the markets. If a disruption activity is performed it will reduce the capacity if the affected market by the percent \(P_{in}\) shown in Table 6. We planned and verified the listed disruption activities with the domain expert to ensure that they simulate real-life disruptions that a trafficker may face.

Activity ‘HE’ targets the high-end commercial sex trade market. The model incorporates the high-end commercial sex trade market by specifically looking at brothels. Research suggests that law enforcement agencies have made previous efforts to target illegal brothels or escort services/sites. Activity ‘LE’ targets the low-end commercial sex market. The low-end commercial sex market is modeled after
selling sex on the street. Law enforcement curbs this by going undercover as sex workers on the street, targeting buyers, or as buyer targeting sex workers. When buyers are arrested and taken out of the market this affects the revenue of the trafficker.

<table>
<thead>
<tr>
<th>Disruption Activity</th>
<th>High-End</th>
<th>Low-End</th>
<th>Theft</th>
<th>Drugs</th>
<th>Fraud</th>
</tr>
</thead>
<tbody>
<tr>
<td>HE</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>LE</td>
<td>0</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>HELE</td>
<td>0.15</td>
<td>0.15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>LEDR</td>
<td>0</td>
<td>0.15</td>
<td>0</td>
<td>0.15</td>
<td>0</td>
</tr>
<tr>
<td>FR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.2</td>
</tr>
<tr>
<td>DR</td>
<td>0</td>
<td>0</td>
<td>0</td>
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*Table 6: Disruption Activities*

Activity ‘HELE’ targets both the high-end and low-end commercial sex markets and could, for example, be an activity that disrupts the demand for commercial sex. Activity ‘LEDR’ targets both the low-end commercial sex market and the drug market. As stated, the low-end sex market and drugs are often intertwined. If law enforcement were to go undercover as street buyers of sex or drugs, they would subsequently decrease street-based activities.

Activity ‘FR’ targets the fraud market, which could be done through a government crackdown on benefits fraud through either increased fraud investigations, more stringent requirements, or both. Activity ‘DR’ targets solely the drug market. It is widely known that there is an opioid epidemic sweeping the nation. Rather than prosecuting drug users, the government looks to transition to treating users as mental health patients and offering them the appropriate rehabilitation needed. Additionally, the government has begun to target drug dealers and charge them with more serious offences. Lastly, activity ‘ALL’ targets all of the illicit markets which can be explained through a Universal Basic Income (UBI). If the legislation is passed, victims will receive the UBI and not need to work the markets as heavily as the UBI will generate revenue for the trafficker.
The budget required to execute a single disruption activity is $1 (a_i)$. Binary variable, $Z_i$, is 1 if the disruption activity is performed, 0 otherwise. Our model accounts for a set of six budget levels, $B = \{1, 2, 3, 4, 5, 6\}$, which allows us to observe and analyze which disruptions the model performs given increased flexibility (3.2.3). For example, at a budget level of 6, the interdiction model can execute 6 of the 7 disruption activities. Additionally, the model is formulated to allow for the removal of a victim from the network at a given budget level, $VB_j$, with binary variable, $Z_v$, if the victim is removed. However, our study sets $VB_j$ at a value greater than any of our set of budget levels focus on the novelty of disrupting trafficking networks through market-level disruptions.

4.2 Results and Analysis

4.2.1 Results and Analysis by City

4.2.1.1 Atlanta

In Atlanta, the model outputs that trafficker revenue decreases, as hypothesized, when the interdiction budget increases (Table 7 and Figure 3). Additionally, the profit is greatest at all levels when the trafficker controls five high-end victims (5H) as opposed to five low-end victims (5L). This aligns with the hypothesis that a trafficker will generate more revenue as the number of high-end victims controlled increases because they can both generate more revenue and work longer hours in their respective commercial sex market. Uniquely, in the 5H network, the revenue generated by the trafficker does not

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Table 7: Revenue of Networks in Atlanta
change between activity budget 4 and 6. If you look at traffickers’ operations, between 4 and 6, they can use the full capacity of their victims in markets that no longer can be disrupted with additional market-level disruptions and, therefore, the profits remain the same. As shown by Figure 3, the slope of the lines between the interdiction budgets decreases as the budget increases with the greatest slope being between interdiction budget 0 and 2. This shows that performing any interdiction activity as opposed to none will significantly negatively affect the revenue generated by the trafficker and there are decreasing marginal utilities in increasing the interdiction budget.

Figure 3: Graph of Revenue of Networks in Atlanta

Table 8 shows that the model favors targeting the high-end commercial sex market as the primary disruption activity when there are high-end victims in the network. In networks with 1 or fewer high-end victims, the interdiction model will perform activities that target the low-end commercial sex markets first. We note that the activity that disrupts both high-end and low-end commercial sex markets is always preferred.
Table 8: Interdiction Activities of Networks in Atlanta

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Table 8: Interdiction Activities of Networks in Atlanta
### 4.2.1.2 Miami

In Miami, the model outputs that trafficker revenue also decreases, as hypothesized, when the interdiction budget increases (Table 9 and Figure 4). The profit is greatest at all levels when the trafficker controls five high-end victims (5H) as opposed to five low-end victims (5L). This aligns with the hypothesis that a trafficker will generate more revenue as the number of high-end victims controlled increases because they can both generate more revenue and work longer hours in their respective commercial sex market.

Uniquely, in the 5H network, the revenue generated by the trafficker does not change between activity budget 4 and 6. If you look at traffickers’ operations, between 4 and 6, they can use the full capacity of their victims in markets that no longer can be disrupted with additional market-level disruptions and, therefore, the profits remain the same.

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**Table 9: Revenue of Networks in Miami**
Table 10 shows that the model favors targeting the high-end commercial sex market as the primary disruption activity when there are high-end victims in the network. In networks with 1 or less high-end victims the interdiction model will perform activities that target the low-end commercial sex markets first. These results are like the interdiction pattern shown in Atlanta.

Figure 4: Graph of Revenue of Networks in Miami
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Table 10: Interdiction Activities of Networks in Miami
4.2.1.3 Seattle

In Seattle, the model outputs that trafficker revenue also decreases, as hypothesized, when the interdiction budget increases (Table 11 and Figure 5). The profit is greatest at all levels when the trafficker controls five high-end victims (5H) as opposed to five low-end victims (5L). This aligns with the hypothesis that a trafficker will generate more revenue as the number of high-end victims controlled increases because they can both generate more revenue and work longer hours in their respective commercial sex market. Uniquely, in the 5H network, the revenue generated by the trafficker does not change between activity budget 4 and 6, for similar reasons as explained in the Atlanta and Miami results.

Table 12 shows that the model favors targeting the high-end commercial sex market as the primary disruption activity when there are high-end victims in the network. In networks with 1 or less high-end victims the interdiction model will perform activities that target the low-end commercial sex markets first.

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Table 11: Revenue of Networks in Seattle
Figure 5: Graph of Revenue of Networks in Seattle
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Table 12: Interdiction Activities of Networks in Seattle
4.2.2 Results and Analysis by Network

We now focus on analyzing the differences between interdiction strategies and trafficker profits for each type of network.

4.2.2.1 Network 5H

Figure 6 shows the profits of the traffickers for networks with 5 high-end victims. The graphs of Atlanta and Seattle overlap when there are five high-end victims in the network. This is because the revenue per hour of the high-end commercial sex market is identical in these two cities ($200/hour). The revenue generated by a trafficker in Miami is significantly near half the revenue generated in Atlanta and Seattle due to the low profitability in Miami of high-end commercial sex ($100/hour).

![Graph of Cities in Network 5H](image)

*Figure 6: Graph of Cities in Network 5H*
4.2.2.2 Network 4H, 1L

Figure 7 shows the profits of the traffickers for networks with 4 high-end victims and 1 low-end victim. The graphs of Atlanta and Seattle are nearly identical in this network. The trafficker in this network operates with four high-end victims and only one low-end victim. Being that the revenue generated in the high-end commercial sex market is identical in Atlanta and Seattle, but less in the low-end commercial sex market in Seattle when compared to Atlanta it is clear that the trafficker in Atlanta will have slightly higher larger revenues.

Figure 7: Graph of Cities in Network 4H, 1L
4.2.2.3 Network 3H, 2L

Figure 8 shows the profits of the traffickers for networks with 3 high-end victims and 2 low-end victims. The graphs of Atlanta and Seattle begin to express clear separation as more low-end victims are added to the network. It’s of note that the revenue gap significantly decreases between Atlanta and Seattle as the interdiction budget increases. This is due to the trafficker’s heavy reliance on high-end victims, as they are increasingly disrupted there is more reliance on other illicit activity market where the revenues generated by those are constant across the cities. Additionally, the decreasing slope of the Miami data is noticeably less than the slopes of Atlanta and Seattle between all budgets. This is attributed to the smaller range between the revenue of high-end commercial sex market and the revenue low-end commercial sex market revenue in Miami, so the disruption activities do not affect revenue as much as in the other cities nor due changes to the profiles of the victims in the Miami trafficking networks.
4.2.2.4 Network 2H, 3L

Figure 9 shows the profits of the traffickers for networks with 2 high-end victims and 3 low-end victims. The graphs of Atlanta and Seattle show a clearer separation as an additional low-end victim is added to the network. Like Network 3H, 2L the decreasing slope of the Miami data is noticeably less than the slopes of Atlanta and Seattle between all budgets.

![Graph of Cities in Network 2H, 3L](image)

4.2.2.5 Network 1H, 4L

Figure 10 shows the profits of the traffickers for networks with 1 high-end victims and 4 low-end victims. This network shows the clearest separation of the plots thus far. This network leans heavily on low-end victims where revenue generated from low-end victims from most to least is Atlanta, Seattle, and Miami. There is an inverse relationship between the activity budget and the generated revenue. This is best explained by the model favoring disruption activities that affect the commercial sex markets, as those are
decreased the other illicit markets are more heavily worked which generate the same revenue per hour across cities.

\[\text{Figure 10: Graph of Cities in Network 1H, 4L}\]

\[\text{4.2.2.6 Network 5L}\]

Figure 11 shows the profits of the traffickers for networks with 5 low-end victims. This network relies solely on low-end victims, meaning that a trafficker’s victims do not work in the high-end market at all. The difference in revenue generated by the low-end commercial sex market is closer between Miami ($45/hour) and Seattle ($65/hour) than between Seattle and Atlanta ($100/hour). This explains why the revenue of the trafficker in this network is overall closer between Seattle and Miami as opposed to the other networks that resulted in Atlanta and Seattle having more similar values. The profit of Seattle and Miami are very close at budget level 6. This is similarly explained as in previous networks where the model favors disruption activities that affect the low-end commercial sex market. As the ability to operate in that
market decreases the other illicit markets are more heavily worked which conveniently generate the same revenue per hour across cities.

Figure 11: Graph of Cities in Network 5L
Chapter 5

CONCLUSIONS

We aimed to investigate the practical implications of interdiction decisions made to disrupt a human sex trafficking network when a trafficker operates in both commercial sex and other illicit activity markets. The objective was to minimize the profit of a trafficker by executing disruption activities aimed at reducing the capacity in illicit activity markets and by removing victims from the network. In our initial scenario, we modeled a maximization of trafficker profits enabling us to understand the relative effect the network interdictions would have on the profits. Subsequently, we implemented the network interdiction model, limiting both the scope and number of disruption activities to imitate a practical scenario. This shows that performing any interdiction activity as opposed to none will significantly negatively affect the revenue generated by the trafficker and there are decreasing marginal utilities in increasing the interdiction budget.

This model directly replicates inputs made by our Modeling Effective Network Disruptions (MEND) Advisory Group on how sex trafficking networks pragmatically operate. These suggestions highlighting that sex traffickers will force victims to do other illicit activities in addition to their commercial sex work. We worked with a domain expert to that the assumptions, formulation, and input data aligned with a practical sex trafficking network. This is driven by a description of how certain networks operate in real-life, by those who have had significant experience and expertise interacting with those involved with sex trafficking networks. It will be important to analyze the actual profits returned by our model as part of a future data validation phase to understand if it is similar to profits of known sex trafficking networks.
Further research can be done to expand upon this model. In a subsequent study, the budget to remove victims should be considered. Furthermore, like Kosmas et al. (2020) a restructured model would allow a trafficker to respond to interdictions performed by adding new arcs or by having the ability to defend against interdictions. Additionally, it would be interesting to explore the differences required in interdiction resources to implement market-level disruptions compared to removing victims from their trafficking networks. This could help to shed some light to how we should focus disruption activities. Finally, it will be important to examine instances where multiple trafficking networks are all working in the same illicit markets to truly understand the important of these market-level disruption activities.
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