Towards Ethical and Resilient Agricultural Supply Chains: Interdicting Labor Trafficking and Mitigating Disruptions

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Arezoo Jafari

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To my husband.

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List of Acronyms

ADM Archer Daniels Midland Company

AEWR Adverse Effect Wage Rate

AIC Akaike Information Criterion

BIC Bayesian Information Criterion

BLS Bureau of Labor Statistics

BLSIIF Bureau of Labor Statistics, Injuries, Illness, and Fatalities

CSR Corporate Social Responsibility

DHS Department of Homeland Security

DOL Department of Labor

ECM Enhanced Collaborative Model

FLSA Fair Labor Standards Act

GA Genetic Algorithms

GDP Gross Domestic Product

GLM General Linear Model

GLMM General Linear Mixed Model

MCDA Multi-criteria Decision Analysis

MS Management Science

MZINBLM Multilevel Zero-inflated Negative Binomial Linear Model

NAICS North American Industry Classification System

NASS National Agricultural Statistics Service

NB Negative Binomial

NGO Non-governmental Organization

OFLC Office of Foreign Labor Certification

PMF Probability Mass Function

QCEW Quarterly Census of Employment and Wages

OFW Overseas Filipino Workers

OR Operations Research

OSHA Occupational Safety and Health Administration

OJP Office of Justice Programs

OVC Office for Victims of Crime

USDA United States Department of Agriculture

VIF Variance Inflation Factor

WHD Wage and Hour Division

ZINB Zero-inflated Negative Binomial

ZINBLM Zero-inflated Negative Binomial Linear Model

ZIP Zero-inflated Poisson

Acknowledgments

Achieving a meaningful goal demands dedication and perseverance, even when the path is filled with challenges. This dissertation results from years of effort, resilience, and personal growth. It also reflects the invaluable support and encouragement from those who accompanied me on this journey.

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Abstract of the Dissertation

Towards Ethical and Resilient Agricultural Supply Chains: Interdicting Labor Trafficking and Mitigating Disruptions

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Arezoo Jafari

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Committee:

Dr. Kayse Lee Maass, Advisor

Dr. Ozlem Ergun, Committee Member

Dr. Babak Heydari, Committee Member

The food and agriculture industries are critical to the U.S. economy, ensuring the daily food supply while facing significant challenges. These issues include ethical concerns related to labor exploitation and the need to improve resilience against disruptions. Addressing these issues offers an opportunity to create supply chains that are both more ethical and more resilient. This dissertation focuses on two interconnected aspects of agricultural supply chains. The first examines strategies for disrupting exploitative labor practices and ensuring better protection for farm workers. The second explores methods to enhance the resilience of ethical supply chains against various disruptions, including natural disasters and labor shortages. Together, these aspects aim to contribute to the development of agricultural supply chains that are both ethically sound and resilient to disruptions.

Although farm workers play an essential role in the success of these industries, they are vulnerable to labor exploitation and trafficking. Labor violations affecting these workers often go undetected due to limited government resources for inspection. Furthermore, many farm workers face barriers to disclosing their poor working conditions due to their immigration status and mistrust of law enforcement, making them even more susceptible to exploitation. To address this issue, we conducted research to provide strategies for government agencies involved in the H-2A visa program and the screening of H-2A employers to prioritize workplaces for inspection.

In the first study, we employed multilevel zero-inflated negative binomial regression analysis to extract patterns and identify factors correlated with detecting H-2A labor violations. We provide suggestions for improving inspection strategies based on our research results. This involved identifying high-risk locations and labor-intensive worksites with a greater likelihood of labor violations and emphasizing the importance of allocating sufficient task force funding and resources to prioritize inspections in these areas.

Labor trafficking networks in U.S. agricultural supply chains exploit vulnerable workers, including migrants and unauthorized laborers, while evading detection through complex structures, making them difficult to disrupt. In the second study, we developed a comprehensive labor trafficking network model that maps the intricate connections and operations of these networks. Using a bi-level integer programming approach, we optimized intervention strategies to disrupt trafficking operations, balancing resource constraints with the need for maximum impact. By employing K-means clustering, we classified interventions based on their effectiveness, providing clear, data-driven guidance for anti-trafficking agencies to prioritize efforts and allocate resources efficiently. This approach offers a powerful tool for enhancing detection and improving the overall effectiveness of anti-trafficking initiatives in limited resource environments.

The importance of food and agricultural supply chains in our daily lives cannot be emphasized enough. While the prior two studies sought to disrupt exploitative work conditions in agricultural supply chains, this dissertation also seeks to help supply chains that are operating ethically do so in an effective manner. Any disruption in these chains can lead to severe consequences, from food shortages to economic instability. Therefore, it is critical to develop effective strategies to mitigate the impact of disruptions in these non-exploitative supply chains. In the third study, we developed a scenario-based two-stage stochastic model to mitigate the impact of multiple disruptions in agricultural supply chains. This approach enables a detailed evaluation of strategies such as multi-sourcing and the use of backup facilities to reduce disruption impacts. The model incorporates flexibility to handle both partial and full facility disruptions, while accounting for disruptions affecting both primary and backup facilities to provide a comprehensive analysis of supply chain vulnerability and recovery. By employing a multi-period time horizon, the model evaluates supply chain performance over time, considering random disruption start times and the possibility of simultaneous disruptions across multiple echelons with varying severity. The analysis highlights the challenges posed by multiple sources of uncertainty in supply chain decision-making and emphasizes the need for further research to develop actionable strategies for improving resilience in agricultural supply chains.

Chapter 1

Introduction

The U.S. agricultural sector is a critical component of the nation's economy, contributing significantly to economic growth and food security. Agriculture and related industries contribute approximately $1.53 trillion to the U.S. Gross Domestic Product (GDP), accounting for 5.6% of the total economy [1]. Given this substantial economic contribution, it is crucial to build resilience in agricultural supply chains. However, these supply chains often encounter disruptions, such as supply shortages, fluctuations in demand, and logistical challenges. These disruptions can significantly affect their performance and productivity, leading to delays and inefficiencies [2]. Equally important is the ethical treatment of laborers, who are essential to the functioning of these supply chains. Beyond protecting human rights, ensuring fair wages, safe working conditions, and respect for workers' rights also prevents labor shortages and operational disruptions, eventually leading to more resilient and efficient supply chains [3]. Both operational disruptions and labor exploitation are closely linked: ethical treatment of labor supports a sustainable workforce, while operational efficiency ensures efficient supply chain function. Together, they form the foundation for sustainable agricultural supply chains [4]. However, the application of Operations Research (OR) and Management Science (MS) in agricultural supply chains still needs to be explored, especially in managing disruptions and incorporating social and ethical considerations [5]. Bridging this gap can enhance both the operational efficiency and ethical integrity of agricultural supply chains, creating more resilient and sustainable systems [5]. In response to these challenges, this dissertation aims to address the following key research questions:

1. How can I develop ethical frameworks and intervention strategies in agricultural supply chains that effectively disrupt labor trafficking operations, using OR methods to optimize intervention

outcomes?

2. How can I develop effective mitigation strategies to manage multiple disruptions in agricultural supply chains, using optimization models that account for the uncertainty of their impact?

This dissertation addresses these two critical areas. First, I examine the exploitation of vulnerable labor, particularly unethical practices such as labor trafficking and violations of workers' rights, which weaken the integrity and effectiveness of agricultural supply chains. Second, I focus on supply chain disruptions, whether they arise from supply-side shortages or transportation delays, that reduce the resilience and efficiency of food production and distribution [6]. By addressing these interconnected challenges, this research aims to reduce exploitative labor practices and manage risks that threaten the strength of agricultural supply chains, ultimately building systems that are both operationally robust and ethically sound.

To address the first research question, it is essential to understand the vulnerability of laborers, particularly migrant workers, within the agricultural sector. Migrant farm workers play a crucial role in the U.S. agricultural supply chain, contributing a significant portion of the labor force [7]. However, when these workers are excluded from labor rights protections and benefits programs, employers may benefit from reduced labor costs, but at the expense of the workers' well-being [7]. This exclusion leaves migrant workers vulnerable to exploitation, including poor living conditions, wage theft, unsafe work conditions, and excessive working hours, which raise serious ethical concerns and threaten the long-term stability of the agricultural workforce.

In this research, I conducted two studies aimed at addressing labor exploitation within agricultural supply chains. The first study identifies factors correlated with detecting labor violations, offering valuable insights that inform intervention strategies to help government agencies prioritize inspections and investigations. The second study introduces a novel labor trafficking network model within agricultural supply chains, mapping the complex interactions between traffickers and interdictors (anti-trafficking stakeholders). This framework highlights how traffickers attempt to evade detection while interdictors strategically intervene to enhance the effectiveness of their efforts, ultimately increasing the detection rate of trafficking operations. By examining the uncertainties in the effectiveness of various intervention strategies, whether implemented by an individual interdictor or through collaborations among multiple stakeholders, this study provides anti-trafficking stakeholders with critical insights to make informed decisions about detecting and disrupting trafficking operations. Together, these studies contribute to a deeper understanding of labor exploitation and offer practical solutions to improve worker protection and reinforce the ethical standards of the agricultural industry.

The second part of this dissertation shifts focus to addressing the challenges outlined in the second research question. Agricultural supply chains are exposed to a range of disruption risks, including supply or demand disruptions and transportation challenges, all of which threaten their resilience and require structured strategies for enhancing adaptability and mitigate these risks [2, 6]. Examples of these disruptions include labor shortages [8], climate change [9], natural disasters such as floods and earthquakes [10], fluctuating market demand [11], trade restrictions, and logistical bottlenecks such as road closures or border crossing delays [12]. In the third study of this dissertation, I developed a two-stage stochastic model focused on mitigating the impact of disruptions in the wheat supply chain, a multi-echelon system crucial to agricultural production. The model developed evaluates facility selection, determining whether facilities should serve as primary or backup options, and optimizes resource allocation strategies over a multi-period horizon. To mitigate uncertainties, the model incorporates various disruption types, including differing durations, capacity reductions, and unpredictable start times, reducing their overall impact. Through this approach, the study aims to enhance the resilience and sustainability of the agricultural supply chain by addressing the uncertainty surrounding the effects of disruptions.

This dissertation offers a multifaceted approach to improving the resilience of the agricultural supply chain by addressing the need to mitigate the impact of disruptions and the critical importance of combating labor exploitation. The integration of strategies that address operational risks while promoting ethical labor standards highlights the broader goal of creating supply chains that are both resilient and socially responsible. In addition to the exploitative work that some employers employ on a day-to-day basis, operational disruptions may further contribute to circumstances that increase the risk of labor exploitation. During events like the COVID-19 pandemic, disruptions in the agricultural supply chain significantly impacted working conditions, including lack of social distancing, reduced access to healthcare, and diminished worker safety [13, 14]. Additionally, such disruptions can affect workers' wages and working hours, as employers facing economic pressures may attempt to minimize costs, which can lead to adverse impacts on labor conditions. These interconnections suggest that operational stability and ethical labor practices create a resilient supply chain [15].

The well-being of laborers is crucial for the sustainability of agricultural supply chains [3, 16]. Production or activities within the supply chain can only occur with a reliable and healthy workforce. When workers, especially migrant laborers, have access to essential rights such as healthcare, fair wages, and safe working conditions, it not only improves their productivity but also strengthens the supply chain by reducing disruptions caused by labor shortages or poor working conditions [3]. This is particularly true during operational disruption, such as the COVID-19 pandemic, when the resilience of the labor force plays a pivotal role in maintaining consistent operations [3].

This research makes several significant contributions to addressing ethical and operational challenges in agricultural supply chains, both from a contextual insight perspective and from an OR methods perspective.

The first contextual insights come from a multilevel zero-inflated model was used to identify critical factors correlated with detecting labor violations across U.S. states, providing valuable insights into the factors that have correlations with the prevalence of labor violations among farm workers. This enables stakeholders to target enforcement efforts more effectively. Second, a comprehensive labor trafficking network structure was developed and modified explicitly to fit the agricultural sector's unique dynamics. The model explores recruitment methods, worker profiles, entry points, and exploitation tactics within agricultural labor trafficking networks within the United States.

From an OR methodology perspective, this dissertation introduces a new bi-level integer programming model that evaluates individual and collaborative interventions to detect labor trafficking while accounting for the uncertainty of intervention impacts. Additionally, a two-stage stochastic multi-echelon supply chain model was developed to mitigate disruptions at various echelons of the agricultural supply chain. The model incorporates a broad range of potential supply chain interruptions by generating random scenarios with variations in the start time of disruptions, facility capacities post-disruption, and disruption durations across three impact categories (low, medium, and high). This detailed approach enables the evaluation of mitigation strategies under diverse conditions, providing a comprehensive framework for decision-makers to enhance the resilience and adaptability of agricultural supply chains in the face of unpredictable disruptions. Together, these contextual and methodological contributions offer practical strategies to enhance the sector's ethical standards and operational resilience.

The following chapters are structured to present the key findings of this research. Chapter 2 begins by addressing the vulnerabilities of farm workers to labor violations through a comprehensive literature review of factors that may be related to the count of labor violations detected across the U.S. It then presents significant insights by applying a multilevel zero-inflated model to identify critical factors correlated with detecting labor violations, highlighting states and industries with a higher risk of such violations. This analysis offers insights that can help anti-trafficking stakeholders increase their detection and intervention efforts, enabling them to allocate their limited budget and resources more effectively to areas where labor violations are more likely to be detected.

Chapter 3 explores the challenges of mapping the complex structure of labor trafficking networks in agricultural supply chains, based on real labor trafficking cases. Using a bi-level network interdiction model, this chapter examines the strategic interaction between traffickers, who aim to avoid detection, and anti-trafficking stakeholders, who work to enhance detection efforts. The analysis provides key insights into intervention strategies to combat trafficking within the agricultural sector.

Chapter 4 introduces a two-stage stochastic model for a multi-echelon wheat supply chain operating under multiple disruptions with multiple sources of uncertainty, including the impact of disruptions,start times, and affected facilities. The model, solved using Benders decomposition, provides long-term mitigation strategies aimed at reducing the impact of these disruptions on the agricultural supply chain, including primary and backup facilities and multiple sourcing.

Finally, Chapter 5 concludes the dissertation by summarizing the findings on enhancing the resilience of agricultural supply chains. This chapter discusses the implications of studying labor trafficking networks and intervention strategies to improve workers' conditions, as well as addressing multiple sources of disruptions in ethical supply chains. It also offers recommendations for future research directions.

Chapter 2

Enhancing Detection of Labor Violations in the Agricultural Sector: A Comprehensive Analysis

2.1 Introduction

The U.S. agricultural industry is crucial for ensuring food security and contributing to the national economy. This industry comprises various sectors, such as crop production, livestock farming, and food processing. However, it faces numerous challenges such as labor shortages [17], climate change [18], and a growing demand for sustainable practices [19]. As a result, there is an increasing need for migrant farm workers.

Migrant farm workers are essential for fulfilling the labor demands in the U.S. agricultural sector, particularly in seasonal and labor-intensive areas. International migrants occupy a significant portion of entry-level jobs in agriculture [7]. Employers often cite the lack of qualified local workers, the superior work ethic of migrants, and, occasionally, the lower labor costs associated with migrant workers as reasons for their preference. This is especially true when migrants are excluded from pension and other benefit programs, which can add 20 to 30 percent to labor costs [7]. However, migrant workers are susceptible to exploitation, as they face job-related risks, such as exposure to farm chemicals, substandard living conditions, and violations of work hours and wages.

To address labor shortages in the agriculture industry, the U.S. has implemented the H-2 (and, since 1986, the H-2A) visa programs since 1952. These programs enable farmers to fill seasonal farm jobs with guest workers from other countries when they anticipate a shortage of domestic workers, including U.S. citizens, other legally authorized workers, and undocumented workers. Employers seeking to recruit and hire H-2A workers must first obtain certification from the Office of Foreign Labor Certification (OFLC) of the U.S. Department of Labor (DOL) [17]. It is important to note that the H-2 programs are not new phenomena but rather part of a long history of the United States relying on low-paid workers to support the agriculture industry, beginning with slavery and progressing through sharecropping and the Bracero program, which brought workers from Mexico to fill the labor needs in agriculture.[20, 21]. It should be noted that not all H-2A workers face exploitation, yet the history of labor exploitation impacts the H-2A program, necessitating ongoing efforts to enhance labor protections.

Farm workers on H-2A visas are an essential component of the agricultural industry, as indicated by the rapid increase in H-2A workers employed in the U.S. agricultural industry over the past decade [22, 23]. Most agricultural industries have experienced significant growth in H-2A employment, particularly in industries with high labor requirements and seasonal employment [22]. From fiscal year 2010 to 2020, the number of jobs certified for H-2A worker employment increased from approximately 75,000 to 275,000. Six states comprised 55 percent of these H-2A certified jobs: Florida with 14 percent, Georgia and Washington each with 10 percent, California at 9 percent, North Carolina at 8 percent, and Louisiana at 4 percent [24]. Around 80 percent of job certifications in fiscal year 2020 lead to the issuance of visas for H-2A workers. However, not all employers complete the hiring process for H-2A workers, and certain workers may occupy more than one certified role.

While H-2A policies state that H-2A workers must receive certain benefits not consistently afforded to non-H-2A agricultural workers, such as required workers' compensation coverage [25], these benefits don't always come to fruition. Additionally, H-2A workers are limited to working for the employer who applied for their services through the DOL. However, during the COVID-19 pandemic, temporary changes were made to the Department of Homeland Security (DHS) requirements for H-2A change of employer requests and H-2A maximum period of stay exceptions [26]. This restriction, coupled with language barriers, lack of knowledge about their rights, and limited access to legal assistance, leaves workers with few options if they encounter abusive work conditions or wage theft. In situations of abusive labor experiences, their only option is to return to their home countries, which they may be reluctant to choose due to losing their job, fear of blacklisting, financial limitations, and other uncertainties. As a result, some workers may feel compelled to continue working under exploitative conditions, leading to workplace abuse [27].

Farm workers who rely on their employment to support themselves and their families often face economic vulnerability and hesitate to speak up for themselves, even in situations that may put their lives at risk [28]. Additionally, their limited financial resources make it difficult for them to access the legal services necessary to assert their rights fully [29]. One of the significant obstacles facing farm workers is their access to health services, as they are exposed to a range of occupational and environmental health risks, which result in high levels of physical injury and illness. The challenges to farm workers' use of health services include inadequate English proficiency, limited education, low income, and a lack of health insurance [30].

Several studies discuss strategies to improve and target efforts to protect farm workers [31, 32, 33]. Farm workers in the United States earn some of the lowest incomes in the labor market and experience a high rate of injuries [31, 34]. The U.S. DOL reveals that the federal and state governments lack the resources for even a one-time inspection of all labor camps in a state [35]. Costa et al. also [31] reported that there is a low probability (1.1%) that each farm employer will be investigated by Wage and Hour Division (WHD) per year. They recommended strategies to target violators, including increasing wage and hour staffing and enforcement funds, targeting the farm labor contractors who are the biggest violators, and ensuring sufficient penalties to stop future violations. Critical to these efforts is understanding factors that increase the risk of H-2A violations.

In this study, we used WHD data that recorded the number of H-2A violations detected by DOL between 2010 and 2020. To examine the factors correlated with the number of H-2A violations, we assembled a dataset containing various factors from multiple sources. This allowed us to pinpoint the factors significantly associated with H-2A violations, thereby offering insights for optimizing resource allocation, such as budget, time, and personnel. Furthermore, the study aimed to prioritize worksites based on the likelihood of labor violations, thereby improving the effectiveness of strategies to address such violations. We employed a multilevel zero-inflated negative binomial model to identify the correlation between factors and the count outcome. Our findings provide valuable insights that can be used by inspection agencies to optimize their investigative strategies, resulting in more efficient and effective enforcement of labor regulations.

Our study makes several contributions to the literature on H-2A violations in the agricultural industry. Firstly, we conducted a literature review to identify the key factors that may be correlated with the detection of H-2A violations. Secondly, while previous studies have used quantitative analyses on certain factors, our study is unique in its application of a multilevel zero-inflated negative binomial model to the best of our knowledge. This approach allows for exploring correlations between significant factors and H-2A violations at both state and industry levels, providing a better understanding of the issue. Thirdly, based on the suggested model, we found that the average size of farms and number of small/medium establishments are correlated with the mean of H-2A violations. Additionally, labor intensity, number of task forces, duration of alleged violations, fatal injury rate, and minimum standard wage are associated with the likelihood of zero H-2A violation counts at both state and industry levels. The poverty rate is associated with both mean of H-2A violations and the likelihood of zero H-2A violation counts. By pinpointing the significant factors associated with H-2A violations, our study offers valuable insights that can guide policy decisions in the realm of labor regulation and enforcement.

The rest of this study is structured as follows: The next Section provides a literature review on factors that may be related to H-2A violations and discusses relevant multilevel and zero-inflated models employed in previous studies. The Data Section details the factors considered for our regression analysis and outlines the data sources used to obtain these variables. In the Method Section, we describe the regression models and multilevel generalized linear models applied to identify correlations between factors and H-2A violation counts. The Result Section presents and interprets our analysis results, emphasizing key factors that significantly correlate with H-2A violations in the agricultural industry. Lastly, in the Discussion and Conclusion Sections, we summarize our findings, discuss the practical implications of our study, and suggest strategies to improve the effectiveness of investigations. Overall, our research provides valuable insights that can inform policy decisions and support the development of more effective approaches for detecting labor violations in this industry.

2.2 Literature Review

This section aims to briefly review relevant studies focused on factors correlated with the risk of labor violations, as well as regression models employed in the analysis of similar data structures.

2.2.1 Factors associated with labor violations among agricultural workers

Many scholars have studied the factors that increase the vulnerability of farm workers to exploitation. Agricultural work environments are notorious for increased risk of occupational injuries due to environmental heat stress, pesticide exposure, heavy workloads, and other workplace safety concerns [36, 37, 38, 39, 30, 40, 41], including fatal injuries [42, 43, 44, 45]. Social distancing was particularly challenging in agricultural workplaces during the COVID-19 pandemic [46]. Prior studies also document the impacts such work environments and stressors have on farm workers' mental health [47, 48, 49, 50]. Additionally, wage violations [51, 52, 53] and violence [54] are widely documented in the agricultural industry. Prior research has explored how these issues are impacted by the contract type and recruitment strategy [55, 31, 22, 56], farm size [57, 58, 59], demographic characteristics of workers [60, 61, 62], migrant workers [35, 22] and labor inspections [63, 64]. We sought to explore the relationship of these factors to the number of H-2A violations detected by the DOL. However, due to the lack of available data on each of these factors during a common time period, our analysis focuses on the subset of factors for which data is available (as described further in the Data Section). Below, we summarize the literature on the aforementioned factors for which data is available and are included in our study. Specifically, we focus on farm size (according to multiple metrics: acreage, number of employees), labor intensity, average net income per farm, poverty rate, and fatal injury rate. We also explore the relationship between the presence of human trafficking taskforces and the state minimum standard wage on detected H-2A violations.

Farm size: Several studies have focused on farm size in relation to labor exploitation. Some have found that labor regulations are less strict for smaller firms (number of employees) [57, 58]. An article examining the impacts of firms' size on the risk of labor violations found a high probability of labor violation among employees in small (less than ten employees) and medium-sized firms (10 to 19 employees) rather than larger enterprises [57].

The literature highlights the importance of considering the correlation between the land size of farms (measured in acres) and labor violations, in addition to the impacts of labor laws on farms with fewer employees. Harrison and Getz [59] found that although larger acreage farms generally offer better job quality than smaller ones, these advantages are disproportionately available to white, U.S.-born workers. Migrant workers face challenges such as job insecurity, limited professional growth, and fear of losing their jobs due to their legal status. The study highlights the need to examine the relationship between farm size and labor violations, considering the varying job quality and opportunities for different worker groups. Larger acreage farms may not always be more prone to labor violations, but specific subgroups like migrant workers could be more vulnerable due to the mentioned factors.

Labor intensity: The main characteristic of high-intensive jobs is the low use of machinery and intensive use of manual labor [65]. These increase workers' exposure to nature and its adversities. Articles have also documented that high-intensive work is highly dependent on temporary migrant workers [22, 66]. One such group of migrant workers that is particularly relevant to this research is workers on H-2A (agricultural) visas. Castillo et al. [22] described the trends in the H-2A program in the agriculture sector, finding H-2A employment growth in vegetables and melons, fruits, and tree nuts that reflect sectors with higher labor intensity. Since migrant workers are susceptible to labor exploitation because of their apprehension about job loss, heightened exposure to hazardous work environments, and extended working hours [67], it is crucial to investigate H-2A violations in labor-intensive workplaces.

Income: The literature highlights the need to examine the correlation between farm income and labor exploitation in the agricultural sector. We could not find articles that specifically identify a relationship between farm income and labor violations in the agricultural industry. However, the literature discussed that businesses maximize labor efficiency to earn profits. This pressure to extract maximum profit from the work process often results in various labor standard issues, such as excessive working hours, low wages, and an over-reliance on contingent migrant workers [68].

Task forces: Barrick et al. [63] studied law enforcement's ability to identify, investigate and prosecute labor trafficking among farm workers. The study revealed a discrepancy between the perceptions of law enforcement, including task forces, regarding labor trafficking operations and the actual reports of labor trafficking by agricultural workers in parts of North Carolina. They recommended that law enforcement agencies in agricultural areas extend their missions to include the protection of laborers, farms, and farm camps in their routine investigations. Farrell et al. [64] explored strategies law enforcement, including multi-agency task forces, can use to improve detection, developing non-traditional partnerships with labor inspections and local regulatory agencies.

Poverty rate: Schwarz et al. [53] presented major clusters of trafficking risk factors, including economic insecurity, house insecurity, education gaps, and migration. They expressed that the relationship between poverty and labor trafficking is strong since poverty restricts people's options and makes them vulnerable to labor exploitation. Also, several studies discussed that the poverty rate influences the chance of children becoming child laborers [69]. Marinescu et al. [51] identified the negative correlation between wages and violations enforced by Occupational Safety and Health Administration (OSHA) and WHD. Nagurney [52] employed a network equilibrium model to demonstrate that wages play a crucial role in decisions to hire migrant workers. The study also revealed that engaging in illicit practices, such as misleading potential workers about their compensation, can financially benefit farmers, thereby emphasizing the need for stricter oversight and control.

Fatal injury rate: Some articles suggest that agriculture is one of the most dangerous occupational sectors regarding fatal injuries [42, 43, 44]. Rivara [45] studied fatal and nonfatal injuries among agricultural workers in the US and found that farm machinery, such as tractors, is the most common reason for fatal and nonfatal injuries.

State minimum standard wages: Fair Labor Standards Act (FLSA) establishes the federal minimum wage and directly elicits the minimum wage provisions for employers to compensate all employees legally. Additionally, the Adverse Effect Wage Rate (AEWR) is a critical component of the H-2A visa program, designed to protect both U.S. and foreign farm workers from adverse impacts on wages due to the employment of H-2A visa holders. Set by the Department of Labor, the AEWR is the minimum wage that employers must pay to H-2A workers and any domestic workers in similar employment to prevent the undercutting of local wage standards [70]. The literature suggests that when the minimum wage increases beyond what a firm can or is willing to pay, maintaining a job match may necessitate paying subminimum wages to some workers [71]. As a result, workers might stop seeking enforcement of the minimum wage, for instance, by choosing not to report violations of minimum wage regulations when they feared their job is in danger [72, 71]. It is important to consider the role of minimum wage standards in labor violations, particularly within the agricultural sector.

2.2.2 Multilevel and zero-inflated models

Multilevel modeling is a robust statistical technique for analyzing data with group structures. This method has been employed across various disciplines to tackle diverse research questions, effectively demonstrating its worth in discerning both within-group and between-group effects and interactions [73]. Multilevel modeling enables researchers to accommodate intricate data structures and has found applications in various social science domains, such as education [74, 75], health [76, 77], environmental studies [78, 79], and violence-related research [80, 81].

Some articles have depicted the linear association between predictors and continuous outcomes by constructing multilevel linear models for detecting significant factors [82, 83]. On the other hand, the generalized linear multilevel models typically utilized for analyzing count, binary, or categorical data differ from the former. Leclerc et al. [84] employed a mixed-effect logistic regression analysis to study the effects of potential guardianship on the severity of child sexual abuse for nested data. Martinez-Schuldt et al. [85] studied the willingness of immigrant community members to notify law enforcement after being victimized. They used multilevel logistic regression analysis for a binary dependent variable.

Several studies particularly focused on count data when the data are clustered or grouped [86, 87, 88, 89, 90, 91, 92], using Poisson distribution [87, 88] or negative binomial distribution [89]. Count data often exhibit excess zeros, meaning there are more zeros in the data than expected from a Poisson or negative binomial distribution. In such cases, two commonly used models are the Zero-inflated Poisson (ZIP) regression model and the Zero-inflated Negative Binomial (ZINB) regression model [90, 91, 92, 93, 94, 95]. Seabright et al. [92] fitted zero-inflated generalized linear multilevel models to investigate the potential impacts of post-marital residence patterns on the size of women's social groups, as well as their access to alloparental childcare among Tsimane fora-ger–farmers in lowland Bolivia. An article presented a ZINB mixed effect model to identify predictors' effects on adolescent victimization [93]. Niedhammer et al. [94] examined the association between psychosocial work factors and sickness absence in 31 Europe countries. They used the multilevel negative binomial hurdle model to study the count of sickness absence with three hierarchical levels and excessive zeros. Using the zero-inflated negative binomial model with random effects, Forst et al. [95] modeled the association between factors, including the occupational category and demographic characteristics, and work-related injury counts for repeated measures within zip codes. This study provided evidence to support the potential benefits of community-based approaches for reducing the burden of workplace injuries and promoting occupational health and safety.

Our study employs multilevel and zero-inflated models as valuable tools for understanding the factors associated with H-2A labor violations. Leveraging a unique dataset, our analysis contributes to the existing literature on the factors that are correlated with H-2A labor violations. In addition, multilevel modeling is particularly advantageous for our research, as it accounts for varying predictor effects across categories, such as state or industry. This observed variation in our data allows for a more accurate assessment of the relationship between these factors and H-2A violation counts compared to previous methods. Furthermore, we incorporate a zero-inflated model in our study to address the presence of structural zeros in the data. This is essential for our analysis, as there are likely two distinct mechanisms generating detected H-2A violations, one of which does not produce detected violations greater than zero count. The zero-inflated model accurately accounts for these structural zeros, offering a more comprehensive understanding of the factors that are correlated with H-2A labor violations.

2.3 Data

The data used in this analysis comes from multiple sources, which are described in detail in this section. We also discuss the data cleaning process and feature selection to identify the most important factors used in the regression analysis.

2.3.1 Data collection

This research utilizes data from multiple sources to examine the correlation between various factors and H-2A visa program violations, which could help inform policymakers and inspection agencies in detecting violations in the agricultural industry. To analyze labor violations in the agricultural sector, we used data from the WHD of the U.S. DOL covering the period from 2010 to 2020 [96]. Specifically, cases with a "findings start date" and "findings end date" between 2010 and 2020 were included. The dataset includes information on multiple types of violations, such as H-2A, H-1A, H-1B, Occupational Safety and Health Administration, and Fair Labor Standards Act violations, per case, investigated by DOL. Investigations are initiated in multiple ways. In addition to proactively targeting industries known for high violations or where vulnerable workers and low-wage challenges are prevalent, the WHD receives confidential complaints that initiate investigations [97]. Given this context, this study aims to explore the correlation between various factors and the H-2A violation count to provide insights that could enhance the precision of these investigations. The dataset includes 175,126 cases investigated by DOL in a wide range of industries. Given our research's focus on labor violations in the agricultural sector, we relied on a specific subset of data related to the count of H-2A violations per case. Specifically, the data was filtered to include only those cases with North American Industry Classification System (NAICS) codes that began with 11, corresponding to agriculture, forestry, fishing, and hunting industries. This filtering ensured that the analysis focused specifically on labor violations in the agricultural sector where H-2A violations may occur and resulted in 12,041 remaining cases. We next excluded H-2A violation counts for Puerto Rico and the District of Columbia from our analysis as our study focused on the 50 U.S. states. Additionally, finding data on relevant factors for these regions was challenging. This further reduced the number of cases from 12,041 to 11,976. Of the 11,976 cases within the 50 U.S. states with NAICS code starting with "11", 2,523 were found to have greater than zero H-2A violations reported. However, it is important to note that for the cases with zero H-2A violations reported, it is unclear whether the DOL investigated for H-2A violations and found no violation occurred or whether DOL focused on investigating other types of labor violations and therefore was not looking for H-2A violations. This presented a challenge for the analyses, and we explained in detail how we addressed it in the methodology section. Additionally, some cases were found to have multiple H-2A violations. Thus, the 2,523 cases with non-zero H-2A violations had a total of 73,781 H-2A violations.

H-2A violations were found in all 50 states and 17 of the 19 agricultural industries over the 10 year period analyzed (see Figs 3.1 and 3.3, respectively). Florida, California, and Nevada clearly show more H-2A violations than other states. However, it is worth noting that factors such as the number of H-2A workers employed, number of farms, climate, and population of these states may contribute to the higher number of violations and that Fig 3.1 provides the count of H-2A violations identified without normalizing for these factors. Indeed, when accounting for the number of H-2A workers certified in each state (see Fig 3.4), Nevada continues to display more violations than other states, while Florida and California have a more moderate number of violations per H-2A worker certified. New Mexico, Kansas, and Alaska also have a substantially higher number of normalized H-2A violations than most states (Fig 3.4, although they have a low H-2A Violation Count (Fig 3.1)). Note that the dataset for the number of H-2A workers certified in each state does not reliably report the sector of the business seeking certification, so Fig 3.4 focuses on H-2A violations and certifications for all industries. Since the H-2A visa is an agricultural visa, a vast majority of the identified H-2A violations are within the agricultural sector (i.e., NAICS code beginning with '11'). Therefore, it is not surprising that the distribution of H-2A violations identified within the agricultural sector (Fig 3.1) closely resembles the distribution of H-2A violations identified in all sectors (see Appendix A).

The bar chart reveals that substantially more H-2A violations have been identified in the Support Activities for Crop Production (19,950), Vegetable and Melon Farming (18,727), and Fruit and Tree Nut Farming (17,073) industries than in other agricultural industries; some industries have had very few H-2A violations identified, such as Poultry and Egg Production (96), Forest Nurseries and Gathering of Forest Products (52), Logging (14), and Hunting and Trapping (2). No H-2A Violations were identified in the Fishing and Timer Tract Operations industries during the 10 year period. This is not particularly surprising, as the notable disparity in the incidence of H-2A violations among distinct agricultural sectors can be attributed, to some extent, to the level of H-2A employment within each industry. The combined analysis highlights geographical and industry-specific H-2A violation trends.

We combined WHD data with external data from multiple sources to form our consolidated dataset. The external data consists of various factors that we categorized into three groups: agriculture land, inspection, and population, see Table 3.1. Several studies in the Literature Review Section that discussed the potential factors related to the vulnerability of farm workers motivated us to study their impacts on the number of H-2A violations. In the following paragraphs, we describe the factors

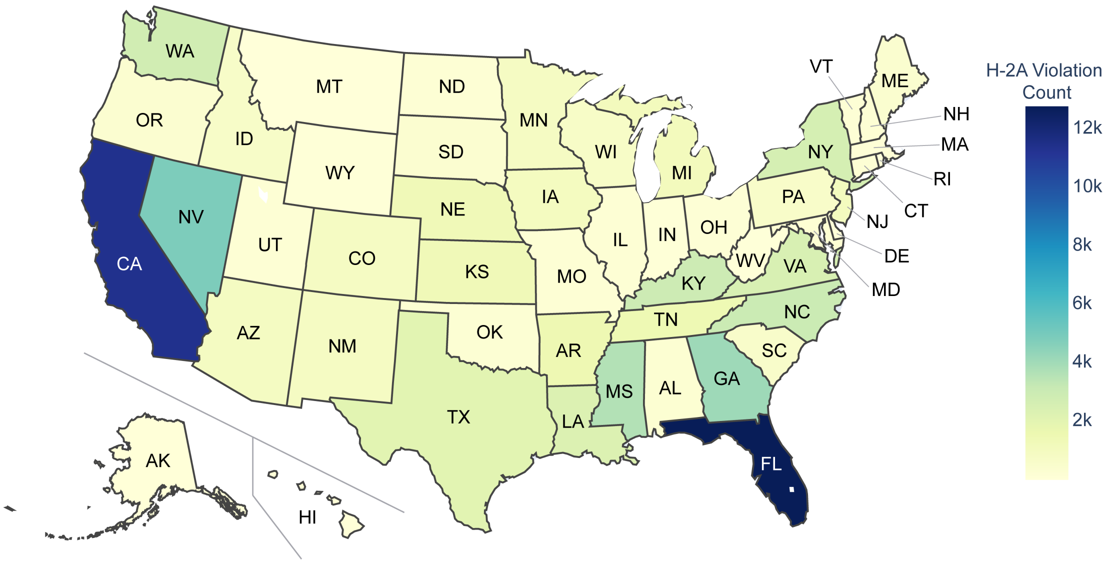


Figure 2.1: Geographical distribution of H-2A violations. The heatmap illustrates the total number of identified H-2A violations within the agricultural sectors per state from 2010 - 2020.

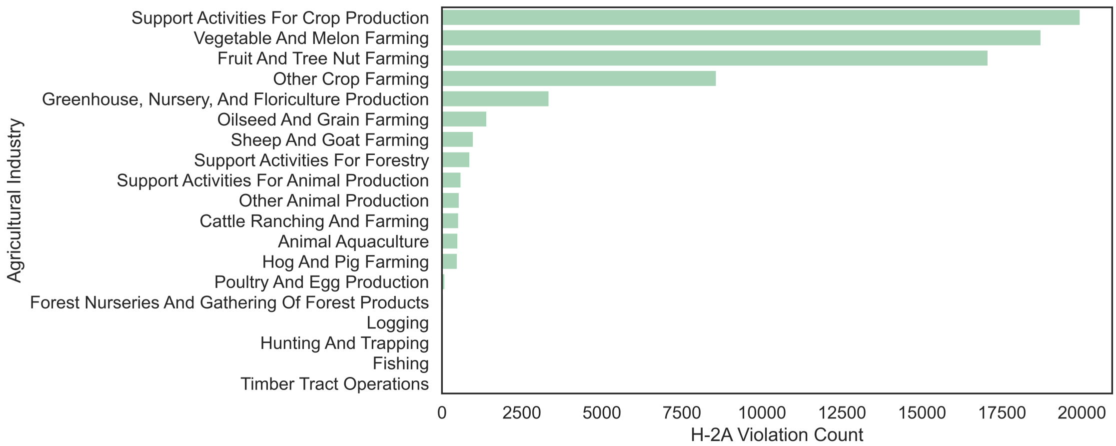


Figure 2.2: H-2A violations by industry. The bar plot demonstrates the distribution of H-2A violation counts across agricultural industries, highlighting the industries with the most violations from 2010 - 2020.

considered in the analysis.

Average size of farms (acres) – Each state's average acreage size of farms was collected from the United States Department of Agriculture (USDA) database from the National Agricultural Statistics Service (NASS) [98] using the `Average farm size (acres)` field. The data rep-

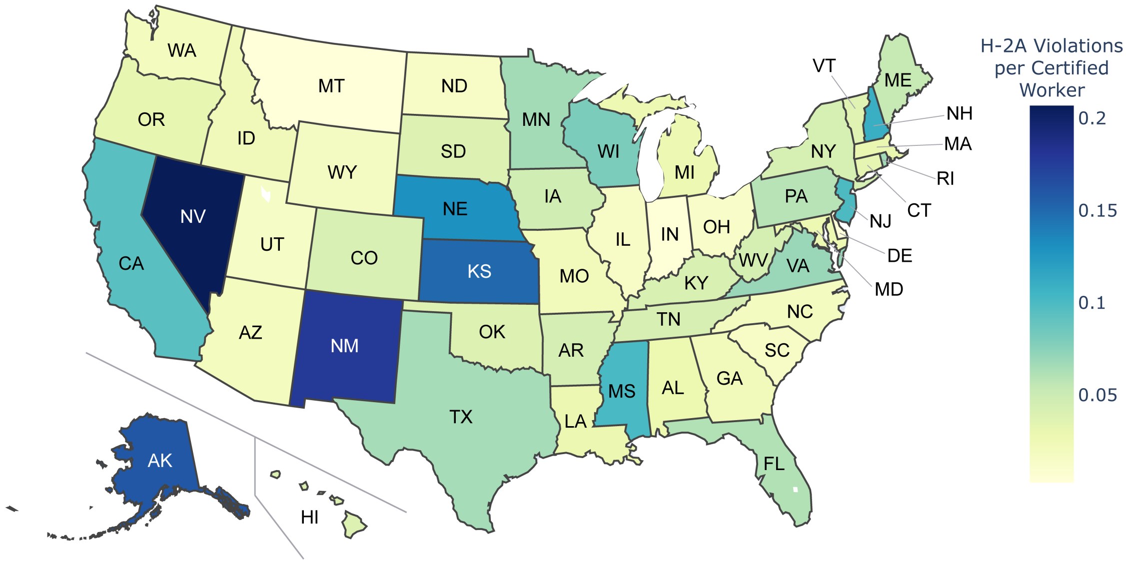


Figure 2.3: H-2A violations per H-2A worker certified. The heatmap illustrates the total number of identified H-2A violations (across all industries) divided by the number of H-2A workers certified in each state from 2010 – 2020.

Table 2.1: Data frame

Category	**Factor**
Agriculture Land	Average Size of Farms (acres)
	Number of Farms
	Number of Small/Medium Establishments
	Labor Intensity
	Average Net Income per Farm
Inspection	Number of Task Forces
	Length of Alleged Violations
Population	Poverty Rate
	Fatal Injury Rate
	Minimum Standard Wages

resent the size of any place from which a thousand dollars or more of agricultural products were produced, sold, or normally would have been sold during the fiscal year. We collected data from 2010 to 2020. This dataset contained information for the number of farms, land in farms (acres), and average farm size per state annually. The average farm size ranged from 55 (Rhode Island) to 2745 acres (Wyoming).

Number of farms – The number of farms in each state from 2010 to 2020 was obtained from the NASS USDA database field `Number of farms` field [98]. The number of farms per state ranged from 680 farms (Alaska, 2010-2012) to 248,500 farms (Texas, 2013 & 2017), with an average number of 41,653 farms per state.

Number of small/medium establishments (by number of employees) – The number of small/medium establishments was collected from the Quarterly Census of Employment and Wages (QCEW) database from the U.S. Bureau of Labor Statistics (BLS) [99]. The data represents the employment data from companies in the U.S. by type of industry (NAICS code) and state. It represents the number of establishments recorded quarterly in each year. The data available is only for the number of farms counted in the first quarter of each year. It might exclude H-2A workers depending on the state labor regulation, which is a limitation. Although this data is expected to exclude around 20 % of the agricultural workers, it is considered a representative dataset for operation in the agricultural sector from 2010 to 2020 used in USDA reports [22]. We define small/medium farms as those with less than 20 employees. The justification for this threshold is based on regulations on labor rights. For example, under California law, organizations with less than 26 employers abide by less strict labor regulations, being allowed to pay lower minimum wage [100]. The U.S. Federal legislation exempts the minimum wage for certain organizations. Specifically, organizations with an annual gross volume of sales or business done of at least \$500,000 and specific organizations with fewer than nine employees are exempt from this requirement [101]. Additionally, employees who work for companies with fewer than ten employees do not have the right to receive unemployment insurance [102]. The dataset includes different categories for firm sizes, such as less than 5 employees, 5 to 9 employees, 10 to 19 employees, 20 to 49 employees, and other categories. The dataset comprises various categories for firm sizes, including less than 5 employees, 5 to 9 employees, 10 to 19 employees, 20 to 49 employees, and other categories. As a result, we combined the groups with fewer than 20 employees to represent the small/medium establishment variable, as small/medium-sized firms with less than 20 employees have been defined in a previous study [57].

Labor intensity – To study the effects of labor intensity on labor violation counts, we classified each type of crop in the NAICS code as either high-intensity (1) or low-intensity manual labor (0). A labor-intensive crop is a relative measure of the number of hours of human labor required to produce the same yield in dollars in comparison to other crops [22]. It was difficult to establish a definitive threshold to determine which crops require high-intensity labor due to factors such as technological advancements and changes in farming practices over time [103]. Therefore, we used the same classification as Castillo et al. [22] used in a 2021 USDA report. According to their findings, high-intensive crops usually employ more H-2A workers than non-high-intensive ones [22]. To help improve the classification, we also used other papers to corroborate the classification of which NAICS code is associated with high-intensity labor [31, 103].

Average net income – Net farm income was extracted from the USDA, Economic Research Service, Farm Income and Wealth Statistics [104]. This dataset includes the `net farm income` per state by year for the range of 2010 - 2020. To find the average net income per farm, the net farm income is divided by the number of farms per state by the year. The number of farms is gathered by USDA's reports of farms and land in farms [98]. The average yearly net income varied between -$21,369.12 to $263,372.17 across states.

Number of task forces – Due to the variety of human trafficking task forces throughout the U.S. and a lack of data related to how many task forces exist in each state, we focused on the number of enhanced collaborative model task forces funded through the Office of Justice Programs (OJP), Office for Victims of Crime (OVC) that aim to combat human trafficking [105]. These task forces include victims, law enforcement, social service providers, and other governmental and non-governmental partners to help trafficking victims and provide them with appropriate services. Enhanced Collaborative Model (ECM) task forces have specific provisions focused on labor trafficking, which may provide the best indicator of law enforcement awareness and readiness to identify labor trafficking and associated exploitation. This data consists of information about the funded task forces, award amount, award status (e.g., open, closed, etc.), etc. To transform the data for regression analysis, we counted the unique number of active OVC task forces per by year. The number of OVC funded task forces ranged from 0 to 15 (California, 2019), with an average of 1.002 task forces in a state each year.

Length of alleged violations – We calculated the length of the alleged violations data per case investigated in the WHD dataset by taking the difference of the `findings_end_date` and the `findings_start_date` of the alleged violations [96]. This time period indicates the estimated duration of violations that occurred per case. Only cases related to agricultural businesses (filtered by NAICS codes that begin with 11) during 2010 - 2020 were included in our analysis. To determine the state associated with the business in each case, we used the `st_cd` field in the WHD dataset.

Poverty rate – We obtained poverty statistics by state from The U.S. Census Bureau historical poverty tables [106]. Specifically, we used data from the `Percent in Poverty` field in *Table 19. The number of Poor and Poverty Rate by State: 1980 to 2021* for the years 2010 to

2020. Although we study labor violations in agriculture, due to the lack of available data related to poverty rates specifically for people employed in the agricultural sector, the poverty rate data we used includes households working in agricultural and non-agricultural jobs. The data ranges from a minimum poverty rate of 0.9% (New Hampshire, 2009-2010) to 25.8% (North Dakota, 2012).

Fatal injury rate – As the lack of tracking systems makes detecting and understanding trafficked workers' health and risk patterns difficult, we extract data from the U.S. Bureau of Labor Statistics, Injuries, Illness, and Fatalities (BLSIIF) [34]. According to the data's resources, it can be used to compare risk among worker groups with varying employment levels. Due to incomplete data on nonfatal injuries during our specified timeframe, we relied on the fatal injury rate for our analysis. The data consists of fatal rates across states from 2007 to 2021. However, we used data ranging from 2010 to 2020, which is within the scope of our analysis. The data ranges from a minimum fatal injury rate of 0.9% (New Hampshire, 2009-2010) to 17.7% (North Dakota, 2012).

Minimum standard wages – We used the DOL wage data for changes in basic minimum wages under state law from 2010 to 2020 obtained by the U.S. DOL Division of Fair Labor Standards Act and Child Labor Wage and Hour Division [107]. DOL wage data has some exceptions related to minimum wage values for specific states. To maintain consistency and uniformity in data analysis, we addressed issues by taking the following steps; First, data includes minimum wage values for some states that are lower than the federal minimum wage due to some exceptions, such as a low number of employees. We decided to use the federal minimum wage for states rather than the lowest wage a state can legally pay if all exceptions are met. Second, five states do not have a state minimum wage, which leaves them subject to federal law. We used the federal minimum wage of $7.25 for these states for our analysis [108]. Third, some states have a range of numbers for the minimum wage, indicating that the pay could be anywhere between two numbers. In these cases, we decided to conservatively use the higher value since, in some states, this may indicate the state's initiative to increase wages within their legal framework.

2.3.2 Data pre-processing and feature selection

In this section, we first applied feature scaling to standardize all regressors, as they were initially on different scales. This process ensured that no particular predictor would dominate the analysis due to its scale. To explore the dataset further and identify correlations between regressors or factors, we utilized a correlation matrix, which provided valuable insights into the relationships among the variables.

Table 2.2: Description of factors

Factor	Source	Type	State/Industry
Average Size of Farms	USDA	integer	state
Number of Farms	USDA	integer	state
Number of Small/Med Establishments	QCEW	integer	state
Labor Intensity	USDA, [22]	binary	industry
Average Net Income per Farm	USDA	continuous	state
Number of Task Forces	OJP	integer	state
Length of Alleged Violations	WHD	integer	state and industry
Poverty Rate	USCB	continuous	state
Fatal Injury Rate	BLSIIF	continuous	state
Minimum Standard Wages	DOL	continuous	state

To check for multicollinearity, we employed the Variance Inflation Factor (VIF) to assess the degree of independence among the factors. We discovered that some factors, such as the number of farms, number of small/medium establishments, and average net income per farm, exhibited high VIF values. To select the most relevant features, we employed Pearson correlation analysis and found that the number of small/medium establishments had the strongest correlation with the target variable, outperforming the other two factors. Additionally, we leveraged Feature Importance from the random forest regression model and used recursive feature elimination with k-fold cross-validation to determine the most influential factors for our model. These methods, including the correlation matrix and random forest feature importance, indicated that the number of small/medium establishments should be considered as a factor in our model.

Lastly, we had to select between the number of farms and the average net income per farm based on the VIF results. Since the average net income per farm was derived from the number of farms, we decided to retain the average net income variable, as it implicitly represents the number of farms. This choice allowed us to avoid potential multicollinearity issues while still incorporating valuable information in our analysis.

While no single solution perfectly addresses collinearity, the model selection procedures we used aimed to alleviate the effects of collinearity. This approach focuses on including only variables that have the strongest association with the response variable, selected from a group of correlated predictors. All data cleaning and pre-processing tasks were performed using Python

3.7, ensuring a consistent and robust approach to preparing the data for subsequent analysis. This streamlined process allowed us to efficiently identify and incorporate the most relevant factors into our model, ultimately yielding more accurate and meaningful results.

2.4 Method

In this section, we will explain the modeling approach used to establish a relationship between the predictors and the H-2A violation count, which is the target variable. We begin by exploring various regression models suitable for count data, where many observations have zero counts. Subsequently, we will implement a multilevel model for the grouped data with two levels, state and industry.

2.4.1 Regression models for count data

The dependent variable is the number of H-2A violations detected by DOL for each distinct WHD investigation, which we refer to as a "case". This count denotes the number of workers identified within a single investigation who faced violations. It can only take non-negative integer values and experiences excess zeros. These types of count data are modeled with General Linear Models (GLMs) and General Linear Mixed Models (GLMMs) using either Negative Binomial (NB) or Poisson distributions [109, 110].

We first investigated whether the Poisson distribution would be an appropriate fit for our data by conducting a dispersion test. Upon examining the results, we found that the p-value was statistically significant, indicating the presence of overdispersion in the count data. This overdispersion suggests that the variance is greater than the mean of the outcome variable, which is not ideal for a Poisson distribution. We decided to consider the NB regression model since this model is more adept at handling overdispersed count data, making it a more suitable choice compared to the Poisson regression model. It is common to use a zero-inflated model when there are more zeros in count data than a simple model predicts. To check whether such zero-inflated models are needed, we conduct a model comparison between the simple models and zero-inflated models. Zero-inflated general linear models are a mixture of distributions, one that has degenerate zero counts (logit)—a zero-inflated model—and another that has degenerate integer counts following Poisson and NB distributions—a conditional model [111]. We compared ZINB, and NB models fitted to the dataset using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and likelihood ratio test. AIC and BIC serve as measures for assessing the goodness of fit of statistical models while considering their complexity. Both criteria aim to find the optimal balance between fitting the data well and avoiding overfitting due to unnecessary complexity. Lower values of AIC and BIC signify a better fit of the model to the data, as they indicate a more favorable balance between data fit and model complexity. The formula used to compute AIC is $AIC = -2log(L) + k$, where L is the maximum value of the likelihood function for the model and k is the number of estimated parameters in the model [112]. The BIC penalizes the model complexity more strongly than the AIC, and both are useful for model selection, depending on the trade-off between goodness of fit and model complexity. As shown in Table 2.3, the ZINB model has a lower AIC and BIC value compared to the NB model, indicating the zero-inflated component of the model effectively captures the remaining overdispersion that the NB model does not entirely explain. In addition to AIC and BIC, we used the likelihood ratio test to compare the two models. A likelihood ratio test is a validation approach that compares a simple model, such as the NB model, with a special case of that model that includes the zero-inflated part, such as the ZINB model. According to the test, additional parameters in the ZINB model improve the model's fit significantly compared to the NB model, confirming the conclusion of the AIC and BIC comparison. Therefore, we used ZINB regression for the number of H-2A violations that exhibit overdispersion and excess zeros.

Table 2.3: Performance Comparison: NB vs ZINB Model

Model	**AIC**	**BIC**
$NB\ Model$	30184.2	30265.5
$ZINB\ Model$	28509.4	28664.6

The fitted ZINB model reflects two possible outcomes for H-2A violations reported in this dataset: zero H-2A violations or a positive number of H-2A violations. Some cases reporting zero H-2A violations reflect structural zeros, while others reflect non-structural (random) zeros. Structural zeros encompass cases in which a zero is reported in the dataset because either (a) DOL investigated other (non-H-2A) types of violations; since they were not looking for H-2A violations, no violations were found or reported, or (b) the organization's structure is such that H-2A violations are not possible, such as the organization does not hire H-2A workers. In investigation cases where DOL is inspecting for H-2A violations and the organization's structure is such that a H-2A violation could potentially occur, the reported number of H-2A violations can be zero or greater than zero and are generated using the NB distribution portion of the model. Zero counts in these cases are nonstructural (random) zeros and refer to situations in which the organization could potentially have had violations, but no violation was found because even though DOL investigated for H-2A violations, (a) the organization did not have a violation during the period in which they were investigated or (i.e., true negative) (b) DOL could not detect the H-2A violations that were occurring during the inspection (low detectability) (i.e., false negative).

We assumed that structural zeros occur with probability Φ. Therefore, the Probability Mass Function (PMF) for a ZINB can be formulated as follows [113]:

$$\Pr(\mathrm{Y}=\mathrm{y}) = \begin{cases} \Phi + (1-\Phi)g(Y=0), & \text{if } y=0 \\ (1-\Phi)g(Y=y), & \text{if } y=\mathbb{N}^{+}, \end{cases} \tag{2.1}$$

where the random variable $Y \in \mathbb{N}$ is the count data, y is the realization of Y, and $g(Y)$ is the pmf of the negative binomial distribution. The distribution is formulated in terms of the mean (μ) and dispersion parameter ($\alpha = \frac{1}{r}$), where r is the predefined number of successes that occur according to the definition of the NB distribution.

$$g(Y=y) = Pr(y|\mu,\alpha) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(y+1)\Gamma(\alpha^{-1})}\left(\frac{1}{1+\alpha\mu}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu}{1+\alpha\mu}\right)^{y} \tag{2.2}$$

The negative binomial components are used to estimate the intercept and coefficients of the regression model fitted to the dataset, thereby allowing us to accurately capture the relationships between the variables and make meaningful inferences based on the fitted model.

2.4.2 Multilevel generalized linear models

We explored using ZINB linear models to analyze H-2A violation counts to study the effects of different factors. These factors were explained in detail in Data section. Our data exploration revealed the presence of multiple groups in the dataset, including state and industry. However, we also found that these groups are not hierarchically nested within each other, but instead, they cross [114]. This can be presented schematically for different cases contained within the cross-classification of 50 states by 19 industries, as in Fig 3.5. Cases are at the individual level (level 1), and two higher levels are industry and state (level 2).

Based on the structure of our data, we employed a Multilevel Zero-inflated Negative Binomial Linear Model (MZINBLM) with two crossed random effects – state and industry in both the conditional and ZI parts of the model. We compared the performance of this model with

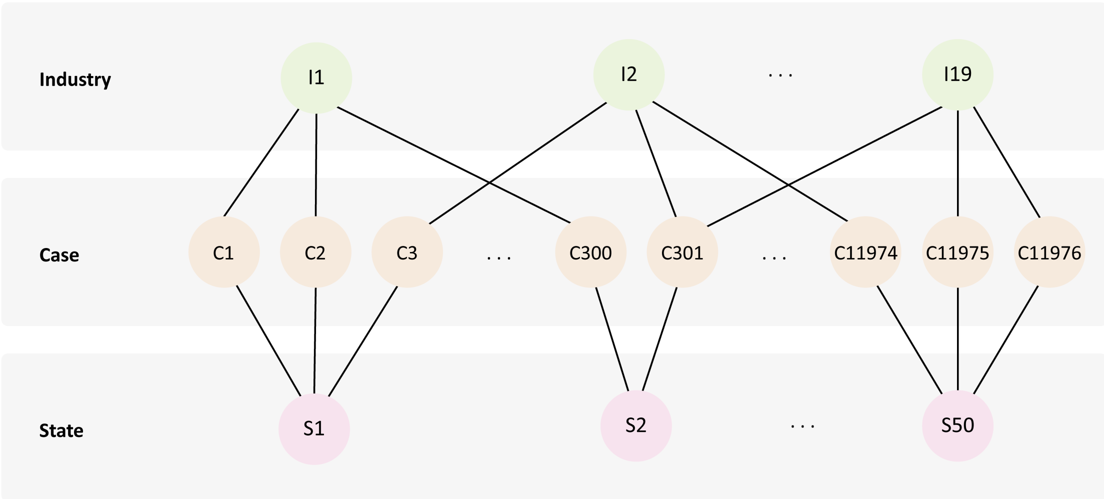


Figure 2.4: Cross-classified data. The multilevel diagram for the cross-classification of two levels of study.

other alternatives, such as the Zero-inflated Negative Binomial Linear Model (ZINBLM) without accounting for state effect or industry effect, MZINBLM with only one level (accounting for either state effect or industry effect but not both), and MZINBLM with two levels (accounting both state and industry) in the conditional model. We evaluated the models by comparing AIC, BIC, and likelihood ratio tests. The findings reveal that the MZINBLM with two crossed random effects in both parts of the model (e.g., conditional and ZI) provided a superior fit to the data as compared to the other models considered, see Table 2.4.

Let $Y_{i(jk)}$ represent the count outcome for the i-th case, belonging to the j-th industry group and k-th state group, $\mu_{i(jk)}$ be the conditional mean of $Y_{i(jk)}$, and $X_{i1}, \ldots, X_{ip}$ be the p predictor variables at the case level. The MZINBLM formulation is as follows [115]:

Level One:

$$\log\left[\frac{\Phi_{i(jk)}}{1-\Phi_{i(jk)}}\right] = a_{i(jk)} + a_1 X_{i1} + \cdots + a_p X_{ip} \tag{2.3}$$

$$\log(\mu_{i(jk)}) = \beta_{i(jk)} + \beta_1 X_{i1} + \cdots + \beta_p X_{ip} + \epsilon_i \tag{2.4}$$

$$\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2) \tag{2.5}$$

Level Two:

$$a_{i(jk)} = a_0 + w_j^{(1)} + w_k^{(2)} \quad \text{for} \quad i = 1, 2, ..., 11976 \tag{2.6}$$

$$\beta_{i(jk)} = \beta_0 + u_j^{(1)} + u_k^{(2)} \quad \text{for} \quad i = 1, 2, ..., 11976 \tag{2.7}$$

$$u_j^{(1)} \sim \mathcal{N}(0, \sigma^2_{u^{(1)}}) \tag{2.8}$$

$$u_k^{(2)} \sim \mathcal{N}(0, \sigma^2_{u^{(2)}}) \tag{2.9}$$

$$w_j^{(1)} \sim \mathcal{N}(0, \sigma^2_{w^{(1)}}) \tag{2.10}$$

$$w_k^{(2)} \sim \mathcal{N}(0, \sigma^2_{w^{(2)}}) \tag{2.11}$$

Table 2.4: Model selection

Model	**Random Effects (Cond Model)**	**Random Effects (ZI Model)**	**AIC**	**BIC**	**logLik**
NB	-	-	30543.4	30624.7	-15260.7
ZINB	-	-	28804.4	28959.6	-14381.2
MZINB1	state	-	28545.2	28707.8	-14250.6
MZINB2	state & industry	-	28423.6	28593.6	-14188.8
MZINB3	state & industry	state	28031.6	28209	-13991.8
MZINB4	state & industry	state & industry	27812.5	27997.3	-13881.3

Where $a_0, \ldots, a_p$ and $\beta_0, \ldots, \beta_p$ are the corresponding regression coefficients for the logit model and conditional model, respectively; $w_j^{(1)}$, $u_j^{(1)}$ and $w_k^{(2)}$, $u_k^{(2)}$ are the random effects of intercept for state and industry respectively, and ϵ_i is the residual error. The variance of the random effects are denoted by $\sigma^2_{u^{(1)}}$, $\sigma^2_{u^{(2)}}$, $\sigma^2_{w^{(1)}}$, and $\sigma^2_{w^{(2)}}$.

The results of this study were obtained using R 4.2.2 with glmmTMB package for multilevel zero-inflated generalized linear models. It includes the conditional model, which is the negative binomial distribution, and the zero-inflated model [116].

2.5 Results

As per the methodology, several models were fit, and their performance was evaluated based on AIC, BIC, and likelihood tests. The best model was selected by comparing the models using these criteria, considering the balance between the goodness of fit and model complexity. We used a multilevel zero-inflated generalized linear model to analyze the count of H-2A violations, taking into account fixed effects such as the average size of farms, number of small/medium establishments, labor intensity, average net income per farm, number of task forces, length of alleged violations, poverty rate, fatal injury rate, and minimum standard wages, as well as crossed random effects from state and industry.

The selected model identified the significant factors associated with the count outcome. Table 2.5 presents the results of the selected MZINBLM, where the first part pertains to the conditional model. This part describes the correlation between the independent variables and the logarithm of the count data, which can be interpreted as the change in the expected H-2A violation counts associated with a unit increase in the corresponding variable while holding all other variables constant. The second part follows that corresponds to the zero-inflation model. This includes log odds of count outcome (estimate) for predicting excess zeros and their corresponding p-values.

The results indicate that the intercept, average size of farms, the number of small/medium establishments, and the poverty rate have a significant correlation with the mean H-2A violation counts in the conditional model. Additionally, the zero-inflated model suggests several factors are significantly associated with the outcome, including labor intensity, number of task forces, length of alleged violations, poverty rate, fatal injury rate, and minimum standard wages. Notably, the average net income per farm is not a significant factor, indicating no significant relationship between this variable and the count outcome.

Upon analyzing the regression results, we noted a positive correlation between the significant factors and the target variable in the conditional model. However, it is essential to note that correlation does not necessarily indicate causation. This relationship may not imply causality due to potential confounding factors, reverse causality, or random variation in the data. Therefore, interpreting these results requires caution, and further research with rigorous study designs and control for confounding factors is needed to establish a causal relationship between these variables. Specifically, a one-unit increase in average farm size correlates with $e^{0.122} = 1.13$ increase in the mean H-2A violation counts. Furthermore, the positive coefficient for the number of small/medium establishments suggests that DOL identified more H-2A violations in states or industries with higher numbers of small/medium establishments (less than 20 employees). The poverty rate is significant in conditional and ZI models. It illustrates that states with higher poverty rates have higher mean H-2A violation counts. According to the ZI model, an increase in the poverty rate is associated with a higher likelihood of structural zero, where no violations are discovered in organizations that are not at risk of H-2A violations. Therefore, it is more likely that zero counts for states with high poverty rates happen due to one of two reasons. First, DOL investigated other violations (not H-2A). Second,

Table 2.5: The multilevel zero-inflated negative binomial linear model

Factor	**Estimate**	**Pr(**$>|z|$**)**
Conditional Model		
Intercept	2.407	$<$ 2e-16***
Average size of farms	0.122	0.006**
Number of small/med establishments	1.369	0.000***
Labor intensity	-0.030	0.921
Average net income per farm	-0.129	0.185
Number of task forces	-0.017	0.559
Length of alleged violations	0.123	0.307
Poverty rate	0.253	0.008**
Fatal injury rate	-0.109	0.169
Minimum standard wages	-0.082	0.159
Zero-inflated Model		
Intercept	2.829	0.000***
Average size of farms	-0.125	0.247
Number of small/med establishments	-0.215	0.821
Labor intensity	-2.386	0.039*
Average net income per farm	0.025	0.838
Number of task forces	-0.066	0.026*
Length of alleged violations	-1.585	$<$ 2e-16***
Poverty rate	1.065	$<$ 2e-16***
Fatal injury rate	-0.725	2.74e-07***
Minimum standard wages	-0.441	1.43e-09***

Significance levels: 0 ***, 0.001 **, 0.01 *

the organization's structure does not require hiring H-2A workers, making it impossible for such organizations to have H-2A violations.

The ZI model also highlights other significant factors such as labor intensity, the number of task forces, the length of alleged violations, the fatal injury rate, and minimum standard wages. The ZI model presents a negative correlation between these predictors and the log of odds ($log(\frac{\Phi}{1-\Phi})$), indicating that increasing one of these predictors is associated with less likelihood of excessive zero (structural zero). The states with higher labor intensity, task forces, length of alleged violations, fatal injury rates, and minimum standard wages are more likely to have nonstructural zeros. Zero H-2A violation counts in these states could happen for two reasons. Although they are at risk of violations, DOL could not detect them. The following reason is that no H-2A violations occurred during the investigation period. Therefore, enhancing inspection methods in these states could lead to more effective detection of labor trafficking.

Our analysis reveals that while specific predictors are consistently correlated with H-2A violations across all areas, the actual levels of these violations vary significantly from one state or industry to another. Each state and industry starts from a different baseline regarding violation frequency. The differing intercepts are significant: they indicate that factors unique to each state and industry also play a crucial role in H-2A violations beyond the predictors we have analyzed. Understanding these unique baselines is essential for enhancing our understanding of the issue. It is important for inspectors to consider these findings within a broader context, combining them with other relevant data to ensure equitable and well-rounded decision-making processes in resource allocation and inspection strategies.

2.6 Discussion

This study presented a multilevel zero-inflated negative binomial regression model to handle cross-classified data with excessive zeros, particularly regarding labor violations in agriculture. We employed a multilevel regression model to investigate the association between different factors and the frequency of H-2A labor violations. The study emphasizes the need for a flexible labor inspection strategy that considers the location and type of agricultural industry.

The ZI model revealed several essential factors correlating with the probability of excessive zeros. Our analysis of DOL's investigations showed that the reasons for zero H-2A violation counts vary depending on the location and the type of agricultural industry. The ZI model's insights suggest that zero counts in industries with higher labor intensity are more likely to occur either because the DOL could not detect the violations or no violation occurred during the investigation. Similar relationships can be observed for other factors, such as the number of task forces, length of alleged violations, fatal injury rate, and minimum standard wages. This study offers valuable insights for labor inspectors and agencies involved in H-2A labor inspections. These findings can guide them in making better-informed decisions regarding resource allocation, encompassing aspects such as budget, the number of inspectors, and inspection time. By doing so, they can enhance the effectiveness and efficiency of resource distribution, particularly in areas with a higher risk of H-2A violations.

This study has several limitations that should be considered. While the regression analysis identified correlations between certain factors and H-2A violation counts, it did not establish causal relationships. Even though establishing causative relationships would be more valuable from a policy perspective, this study is intended as a foundation for such future research. Therefore, future studies should focus on investigating these causal effects, drawing from the insights of this study. Additionally, the absence of comprehensive data related to farm workers, including health issues, access to healthcare, income, housing conditions, and demographic information, limited our dataset construction. As a result, we relied on available data sources. This constraint suggests that our findings should be interpreted carefully, and additional, more extensive research is necessary to gain a deeper understanding of H-2A violations in the agricultural sector.

It is also important to acknowledge that while the DOL plays a role in identifying violations, there is still room for improvement in effectively uncovering abuses. There are numerous reasons why H-2A workers might not report abuses or concerns, and previous research has consistently highlighted the need for more proactive efforts to uncover such abuses. Furthermore, the WHD data we obtained did not clarify whether the DOL conducted H-2A violation inspections in cases with zero counts. This leaves the possibility of undetected or unreported cases, which may have led to an underestimation of H-2A violations in specific states and industries. We attempted to address this issue by using a zero-inflated model to account for excessive zeros. It is also important to note that there are multiple types of rules and regulations H-2A employers are expected to adhere to (including rules related to housing standards, work hours, wage rates, etc.) [117]. However, it is not clear whether non-adherence to all of these rules and regulations results in the type of H-2A violations documented in the WHD dataset. Furthermore, the dataset lacks detailed categorization that would distinguish between the severity of violations, ranging from minor to severe violations. This limitation highlights the need for more detailed data to inform future research and the development of more effective investigation strategies by identifying areas where compliance efforts could be most impactful.

Furthermore, the role of labor contractors is significant within the H-2A program and warrants further exploration. Our current analysis could not delve into this aspect due to the limited detail in the WHD's violation data. This limitation highlights an important avenue for future research, dependent on the availability of more detailed and specific data. However, this highlights the need for improved data collection strategies to better track labor inspections and accurately assess the prevalence of H-2A labor violations.

In addition to the insights that can be gained in this study, the use of H-2A violation data may also provide critical insights into labor trafficking, which is significantly under identified. Though the data is not perfect, it shows the potential for administrative data related to workplace safety and to help inform our understanding of places and situations where workers may be vulnerable to abuses and are in need of protection.

2.7 Conclusion

In conclusion, our study provides essential insights for labor enforcement agencies in shaping specific H-2A violation inspection strategies for each state and agricultural sector. By employing a zero-inflated negative binomial model, this study offers unique insights into the distribution of detected H-2A violations across different states and agricultural sectors. This approach allows us to identify not only states and sectors with high numbers of reported violations but also those with unexpectedly low or zero counts. It is essential to recognize that the absence of H-2A violations in certain states or industries does not necessarily imply that no violations have occurred. For instance, in regions or industries with specific characteristics (e.g., higher labor intensity, number of task forces, length of alleged violations, fatal injury rate, and minimum standard wages), there is a potential for violations to either remain undetected or not occur during official investigations. Additionally, our results highlight the importance of considering factors such as the average size of farms, the number of small/medium establishments, and the poverty rate in planning inspections. Based on our research, states or industries falling within the upper range of these categories have more detected H-2A violations. By providing insights into the state and agricultural sector features correlated to where H-2A violations are currently being detected, our findings may inform future WHD labor inspection strategies regarding where to allocate limited inspection resources.

Chapter 3

Network Interdiction to Improve Labor Trafficking Detection in the U.S. Agricultural Sector

3.1 Introduction

U.S. agricultural supply chains have been repeatedly found to exploit workers through labor trafficking [118]. Despite laws aimed at stopping the use of exploitative practices, trafficking continues to grow within U.S. borders without any sign of abating [119]. To address this humanitarian crisis, several government agencies have been tasked with curtailing labor abuse. However, labor traffickers operate as resilient supply networks that work to evade detection or intervention. Additionally, U.S. agricultural supply chains have a more diverse workforce than most other industries, including migrant farm workers [120], unauthorized workers [121] and U.S. citizens [122]. Due to these complexities, conventional business and law enforcement strategies do not appear to be working at scale to reduce trafficking in corporate supply chains. It is crucial to increase scientific analysis on labor trafficking to prevent this problem and safeguard workers [121, 123]. In this paper, we utilize a network interdiction model to evaluate intervention strategies within the labor trafficking network to understand their effectiveness.

The U.S. has adopted policies to enhance protections for agricultural workers and promotes ethical recruitment practices, particularly within the H-2A visa program [124] which is a temporary work visa for work within the agricultural sector. Anti-trafficking strategies have been part of this approach. In 2010, the U.S. government formed task forces that used the ECM to combat human trafficking [125]. These task forces highlight the ongoing need for collaboration between agencies (local, state, and federal) as well as victim service providers. Anti-trafficking task forces also educate government personnel and communities on how to recognize and report human trafficking [124]. These efforts are further supported by increased worker rights and improved information-sharing across sectors like education, child protection, and occupational health and safety.

While numerous anti-trafficking actions are in place, enhancements are needed such as improving collaborations and information sharing among agencies and increasing trust with vulnerable communities [126]. For example, there is a need to enhance collaboration between the DOL and the DHS to prevent, identify, and remediate labor trafficking efficiently. On a local level, while police and prosecutors acknowledge that labor trafficking exists across various local employment sectors, there is often confusion among both local and federal law enforcement officials about the exact definition that classifies labor trafficking as a criminal offense [127]. To effectively combat labor trafficking, there are calls for law enforcement agencies to enhance training programs and expand routine operations to include focused inspections aimed at detecting labor trafficking [127] and join ongoing collaborative efforts. The necessity for more research is clear, particularly in improving intervention and collaborations to address labor trafficking. Therefore, we propose a network interdiction model to evaluate strategies to detect exploitation within the labor trafficking network to better understand their effectiveness and provide actionable detection strategies to anti-trafficking stakeholders.

While businesses also hope to prevent these human rights violations in their supply chains, they are up against resilient labor trafficking networks. Such illicit supply networks have an almost limitless supply of vulnerable persons to exploit and are adept at continuing their operations while avoiding detection or scrutiny. Though little has been known about such networks in the past, data has recently been collected to robustly understand their operating methods [128, 129] for the purpose of interdicting them.

Network Interdiction Models are a particularly relevant type of OR model for optimizing decisions related to disrupting trafficking networks. Interdiction problems are categorized within a specific subset of two-player bilevel optimization models in which one player attempts to operate as effectively on the network as possible (e.g., maximizing flow [130, 131, 132, 133], taking the shortest path [134, 134], maximize profit [135], evading detection [136, 137, 138, 139, 140]). In contrast, the other player takes actions to hinder their ability to do so. In the context of human trafficking, the interdictor represents an anti-human trafficking stakeholder (such as human trafficking taskforces, law enforcement, federal agencies, service providers, etc.), while the traffickers attempt to operate the trafficking network as effectively as possible. A growing subset of the literature related to disrupting illicit networks focuses on network interdiction models (e.g., sex trafficking: [133, 131, 130, 141], other illicit networks: [142, 143, 132, 137, 136, 138, 139, 140]). Yet, none focus on interdiction models for disrupting labor trafficking.

Given this context, our study develops a comprehensive model of a labor trafficking network that covers the processes victims go through from recruitment to exploitation. Our model is created to illustrate the complex dynamics involved in labor trafficking operations and the relevant behaviors of traffickers within such a network. To generate our model, we analyzed twelve federally prosecuted labor trafficking cases within the U.S. agricultural sector. This approach helped us validate the structure of our proposed supply chain network and ensured that our insights were based on real-world scenarios. Furthermore, these insights were enriched and verified through validation from stakeholders and legal advocates, enhancing our findings' practical relevance and applicability in addressing labor trafficking effectively. We integrate knowledge from criminal justice, business, and operations research fields to generate a generalized labor trafficking supply chain structure represented in node-arc format with the goal of optimizing interdiction efforts to detect and disrupt labor trafficking in the U.S. agricultural sector.

This research aims to assess the impact of coordinated network interdiction models on network disruption. Our labor trafficking network model has similarities to traditional supply chain models; however, the prior focus of supply chain literature has been on preventing disruptions [144, 145, 146, 147], whereas we seek to take actions to disrupt the trafficking networks.

Through a network interdiction approach, we develop a bi-level evasion model that captures interactions between traffickers and anti-human trafficking stakeholders within a labor trafficking network. Focusing specifically on DHS and DOL, we consider a range of interventions they could implement, individually or collaboratively, to improve their ability to detect labor trafficking in the U.S. agricultural sector. We then analyze the effectiveness of individual and collaborative efforts to recommend approaches that effectively combat labor trafficking networks.

Through our analysis, we identify four distinct groups of detection outcomes, namely interventions with minimal, low, moderate, and high impact. We find that moderate and high impact interventions affected a greater number of arcs and extended over more than two echelons within the network. Our analysis also reveals that the effectiveness of intervention strategies is influenced by several factors, including the distribution of arcs, the number of echelons affected, the potential for increased detection rates at each affected arc, and the total number of interventions employed.

Our study makes several contributions to the literature. First, we develop a generalized labor trafficking network structure based on federally prosecuted cases, specifically tailored to the unique dynamics of the agricultural sector. Unlike previous studies that focused on illicit activities within traditional supply chains [148, 149], our model offers a novel analysis of recruitment methods, diverse worker profiles, various entry points into the U.S., and the range of housing conditions and exploitation methods that victims may face in illicit networks. Secondly, our study introduces twelve interventions that can be implemented by stakeholders (i.e. such as DOL and DHS) in response to the scholarly focus on the need for collaborative actions in addressing illicit networks. This approach includes both cooperative and individual agency actions. Thirdly, our study introduces a bi-level integer programming model that integrates both individual and collaborative interventions. This model incorporates the uncertain impacts of multiple interventions, enabling a comprehensive evaluation of the overall detection rate across the labor trafficking network. The clustering analysis of the model results allows us to categorize the interventions into four distinct clusters based on their total detection rates. Our analysis identified unique patterns and characteristics within each cluster, such as the number of interventions and affected arcs and echelons. Notably, the findings reveal several interventions with detection rates closely approaching the most effective strategy, providing agents with valuable insights to select the most suitable strategies based on their available resources.

The remainder of this study is organized as follows: the next section provides a Literature Review on the trafficking networks and discusses models between attackers and defenders. The Labor Trafficking Network Structure section describes the complexities of labor trafficking phases and how we incorporate these into the networks for our model. In Method, we present our bilevel integer programming formulation. Then, we detail the input data and the list of proposed interventions in the Data and Interventions section. The Result Section interprets our findings, identifying the most effective interventions and clustering strategies based on their detection rates. Lastly, the Conclusion section summarizes our findings and explores the practical applications of our research.

3.2 Literature Review

Several recent review papers have highlighted the expanding use of OR and analytics in addressing human trafficking, indicating an increasing awareness of the issue and a rising trend in adopting these methodologies [150, 151, 152, 153]. However, there has been a disproportionate focus on sex trafficking within these studies, and the need to extend analytical methods to address labor trafficking remains evident [152]. Of the few OR studies focused on labor trafficking, the focus of prior studies has been understanding the behaviors associated with labor trafficking and developing diverse strategies to combat it. This includes using supply chain network optimization models that incorporate migrant labor from multiple countries [149]. This paper introduces a novel optimization model to combine a supply chain network with investments to attract international migrant labor in the agriculture sector. Their model's flexibility helps distinguish between wages for national/domestic and international migrant labor, including evaluating the effects of providing accurate versus misleading wage information. Another notable effort is agent-based modeling to reduce wage theft among day laborers with interventions at worker centers [154]. Additionally, a study introduces a non-linear mathematical model to assess the impact of forced labor on supply chain profitability, employing both static and dynamic games that represent the interactions among decision-makers and integrating Corporate Social Responsibility (CSR) within coordination contracts as a critical factor for the first time [148]. All three of these prior studies have considered how exploitation is integrated into the broader licit supply chain, which includes non-exploited labor for a product or service. In contrast, we concentrate specifically on the recruitment-to-exploitation network of labor trafficking victims within the U.S. agricultural sector and contribute to efforts against labor exploitation by offering targeted strategies for enhanced detection.

Other OR methods have been employed to evaluate the impact of interventions on labor trafficking [155, 156]. A notable study introduces a methodology to examine effective anti-trafficking strategies within the Overseas Filipino Workers (OFW) system, using interviews, causal loop analysis, and scenario simulations. This approach determines the dynamics between government policies, worker choices, and economic factors, emphasizing its practicality in real-world applications [155]. The subsequent research utilized a Multi-criteria Decision Analysis (MCDA) approach to analyze labor exploitation risks in specific settlements of migrant workers in the strawberry production sector. This analysis focused on systematically determining the risk levels of these settlements based on diverse criteria [156]. There still exists a significant gap regarding the operational behaviors of traffickers within labor trafficking networks. Our research addresses this gap by evaluating interventions within the labor trafficking network, thus providing new insights and strategies to enhance the effectiveness of efforts against labor exploitation.

From a methodological perspective, a growing subset of the OR literature related to disrupting illicit networks, including human trafficking networks, focuses on network interdiction models (e.g., human trafficking: [133, 131, 130, 141], other illicit networks: [142, 143, 132, 137, 136, 138, 139, 140]). Interdiction problems are categorized within a specific subset of two-player bilevel optimization models in which one player attempts to operate as effectively on the network as possible (e.g., maximizing flow [130, 131, 132, 133], taking the shortest path [134, 134], maximize profit [135], evading detection [136, 137, 138, 139, 140]), while the other player (the interdictor) takes actions to hinder their ability to do so. In the context of human trafficking, the interdictor represents an anti-human trafficking stakeholder (such as human trafficking taskforces, law enforcement, federal agencies, service providers, etc.), while the traffickers attempt to operate the trafficking network as effectively as possible.

In this paper, we seek to identify which set of interventions the interdictors should implement to most effectively detect and disrupt labor trafficking. Thus, network interdiction models in which the defender seeks to evade detection and the interdictor aims to reduce their likelihood of evading (i.e., min-max evasion network interdiction models) are most relevant to our study. Examples of such models involve smugglers attempting to evade detection within a transportation network and interdictors installing radiation sensors to reduce evasion chances. The stochastic network interdiction model considers the smuggler's route as probabilistic at the sensor installation time, illustrating the complexities of intercepting illicit activities [137, 139]. Our model broadens the scope of labor trafficking, featuring multiple interdictors with varied interventions and examining the uncertainties in their effectiveness, providing insight into disrupting trafficking networks.

Another study in the literature demonstrates the use of min-max evasion models within an illicit product distribution in a network defined by multiple commodities. It addresses a maximum flow interdiction problem where law enforcement, constrained by a limited budget, strategically engages with a hierarchically organized network of traffickers. The focus is on disrupting the trafficking flow by targeting lower-level members for arrest or surveillance, aiming to minimize traffickers' profits over time [142]. In the study mentioned, the interdiction process involves law enforcement observing traffickers over a specified period, leading to potential arrest. Our paper investigates the actions of traffickers within labor trafficking networks more thoroughly. We suggest diverse interventions, from law enforcement training to regulatory inspections, and analyze their impact on decreasing the likelihood of evasion.

However, rather than simply applying traditional network interdiction models to the human trafficking context, the literature indicates a need to adapt traditional methods to better align with the complexities of the human trafficking context [151, 150, 153, 157]. For example, a comprehensive network that accurately captures the behavior of trafficking operations is crucial for understanding how traffickers manipulate victims, covering their recruitment and exploitation methods. This includes the strategies that traffickers use to bring victims to their destinations, the various types of exploitation at worksites, and illustrating why victims might find it difficult to leave.

The model must also reflect traffickers' preferences in selecting victims, the transportation process, and managing living conditions. Moreover, it should enable the implementation and evaluation of practical interventions within the network to increase the detection of trafficking actions, including ways to measure the success and impact of these interventions. By integrating these aspects, models can more effectively mirror the complex interactions between traffickers and victims, improving the development of anti-trafficking strategies.

The collaborative efforts of multiple stakeholders, including law enforcement agencies and Non-governmental Organizations (NGOs), play a crucial role in combating human trafficking networks [154, 158]. Such partnerships facilitate the sharing of resources and strategies, enhancing the effectiveness of interventions [154]. Thus, network interdiction models that account for multiple interdictors are increasingly important as they enable a more strategic and coordinated approach to disrupt these complex networks [159, 160, 161, 131]. The paper by [131] advances the interdiction of domestic sex trafficking networks by initially modeling a single interdictor and later incorporating a second interdictor focused solely on victim protection and prevention, which prevents the addition of new victims to the network and protects existing ones from being replaced. Our model extends this concept by addressing the dynamics of labor trafficking, analyzing interventions across different phases of the trafficking process, including recruitment, visa processing, border crossing, housing, and worksites. Our approach uses single and multiple interdictors to target different network segments, exploring the effectiveness of various interventions and identifying the most successful strategies to disrupt trafficking operations. Another study explores the effect of cooperation among agencies on disrupting illicit trafficking networks by assigning specific interdiction responsibilities to various law enforcement agencies based on their operational tier within an overarching network model [160]. It evaluates six levels of coordination separately, from agencies working independently to cooperation among multiple interdictors. While this analysis aligns with our investigation into disrupting trafficking operations, our research goes further by examining diverse interventions implemented by both single and multiple interdictors to improve the detection of labor trafficking activities throughout the labor trafficking network.

The literature review revealed a significant gap in studies explicitly focusing on the collaborative dynamics among stakeholders in labor trafficking networks. To address this, our study explores the complexity of the labor trafficking networks, from the recruitment phase to exploitation. We have developed a list of interventions based on insights drawn from real labor trafficking cases and related reports, modifying our strategies to the unique challenges of this field. Our research contributes a new min-max evasion model that captures the interaction between interdictors and traffickers, evaluating the impact of these interventions on detection rates. This model is innovative in its ability to examine both single and multiple interdictor actions simultaneously, providing an insightful understanding of the effectiveness of various anti-trafficking strategies within the labor trafficking context.

3.3 Labor Trafficking Network Structure

Exploiting workers in the U.S. agricultural sector through labor trafficking is a multi-step process that involves multiple decisions from the trafficker. Motivated by insights from academic and practitioner reports [162, 163, 129], and informed both by a detailed review of federally prosecuted agricultural labor trafficking cases and expert knowledge from anti-trafficking stakeholders, we developed a multi-echelon node-arc representation of the supply chain network traffickers use to recruit labor trafficking victims and exploit them at U.S. worksites.

Specifically, we analyzed 12 labor trafficking cases that were federally prosecuted between 2000 and 2021 and involved labor exploitation that took place in the U.S. agricultural sector. These cases were chosen for their various recruitment tactics, size of the agricultural organization, and information about victims' legal status, offering a diverse picture of labor tracking cases in this sector. Further details on this process and the 12 cases are available in [164] and [165]. We recorded detailed data on recruitment methods, worker characteristics, border crossings and other geographical movements, living conditions, and exploitation at farms, among other details. These data were also supplemented by conversations with anti-trafficking experts, including victim-rights attorneys, prosecutors, government agencies, and labor trafficking victims, to improve and verify the network structure and assumptions.

The resulting multi-echelon supply network is shown in Figure 3.1. Nodes in the top echelon illustrate the various tactics traffickers use to recruit workers into exploitative situations. These include the use of force, fraud, coercion, and/or unlawful fees [127]. This echelon contains 15 nodes, as a trafficker may use a single recruitment tactic or any combination of multiple tactics (e.g., Fo/Fr/Co/Fees). Force refers to using physical harm or threats to compel work. Fraud involves deceptive practices, such as misrepresenting wages or conditions and false jobs. Coercion includes psychological or emotional manipulation, utilizing tactics such as debt bondage, isolation, and control over necessities to exploit workers. Fees cover scenarios where workers are charged excessive recruitment fees, leading to debt bondage as they feel compelled to work off the debts incurred, often under exploitative conditions.

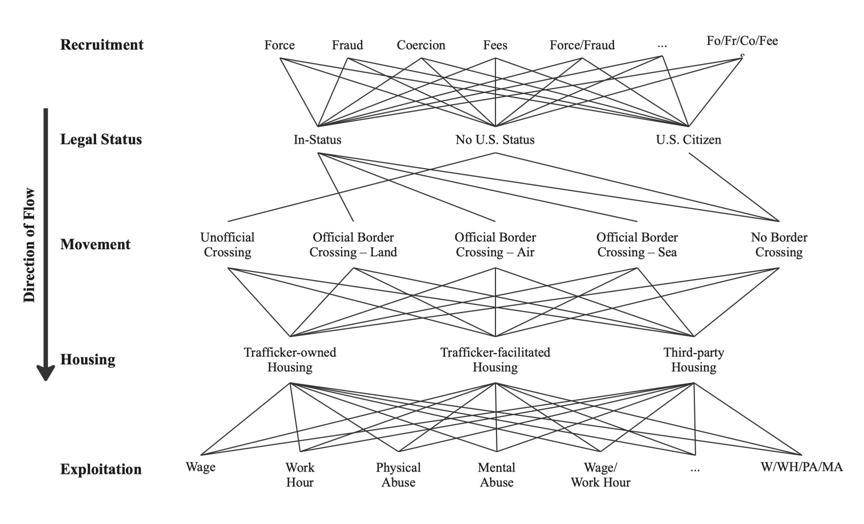


Figure 3.1: This diagram shows the labor trafficking supply network, detailing five echelons from recruitment to exploitation.

Three worker legal statuses found in labor trafficking cases are included: in-status, no U.S. status, and U.S. citizens [127]. Migrant farm workers often fall into the first two categories. Non-citizens who currently have legal authorization to be in the U.S. are regarded as *In-status*. However, non-citizens who do not currently have legal authorization to be in the U.S., who may have either never have had status (e.g., unauthorized workers who crossed the border into the U.S. without a visa) or they might have had legal status at one time but no longer have status (e.g., "overstaying" a visa), fall into the *No U.S. Status* category. U.S. citizens are also included in this network as they can also be in similar exploitative circumstances.

The "Movements" echelon classifies the types of border crossings involved: official border crossings by land, air, and sea; no border crossing needed; and unofficial border crossings [120]. We took care to account for nuances regarding the relationship between a victim's legal status and border crossing as our network is designed to reflect how a victim gets recruited into the job in which they are trafficked, the movement echelon represents the border crossings (or lack thereof) that occur after being recruited into the exploitative job. For example, victims categorized as "In-status" must have crossed into the U.S. through an official boarder via land, air, or sea at some point. However, not all "In-status" labor trafficking victims were recruited into their exploitative work situation prior to entering the U.S. Thus, "In-status" victims who were already in the U.S. on valid visas at the time they were recruited for the agricultural position in which they were trafficked would pass through the "No Border Crossing" node, while those that were recruited while outside the U.S. would pass through the official boarder crossing nodes. As another example, we consider that a person with "No U.S. Status" could have entered the U.S. through an unofficial border crossing with no legal authorization while another victim may have been recruited into the exploitative job after overstaying their visa. In the latter case, the victim with "No U.S. Status" would not need to cross the U.S. border because they were recruited while already in the U.S.

Agricultural workers are housed in a variety of ways, which can significantly affect their living conditions and susceptibility to exploitation [166]. Trafficker-owned housing is directly provided by the trafficker, such as on-site farm housing or a company-owned house. Trafficker-facilitated housing involves arrangements made by the trafficker on behalf of the workers, which could include bookings at hotels. Third-party housing includes housing that is independently owned or rented by the workers themselves.

The last echelon in our model, "Exploitation", capture the four main categories of exploitation observed in labor trafficking: excessive work hours, wage theft, psychological or mental abuse, and physical abuse or poor physical working conditions [120]. Victims often endure long working hours without adequate breaks and may be forced to work overtime without compensation. Many labor trafficking cases also reveal that workers face poor physical conditions and psychological abuse. The physical conditions often involve unsafe environments, such as exposure to toxic chemicals without protective supplies, extreme temperatures without appropriate safeguards, which may lead to health issues such as hearing loss, and respiratory problems. Psychological or mental abuse worsens these hardships, manifesting as verbal abuse, threats of physical harm or deportation and isolation. Financial exploitation is also common, with practices including failing to pay or underpaying wages, delaying payments, and falsifying work hours to reduce wages, and often denying payment for overtime work. The 15 nodes in this echelon reflect that victims may experience one or a combination of these types of exploitation.

This resulting network illustrates key steps in the process of recruitment to exploitation. We next describe how this network can be used to determine a set of interventions resource-constrained anti-trafficking stakeholders can take to maximize their chances of detecting trafficking within the network.

3.4 Method

3.4.1 Problem description

Network interdiction models offer a way to analyze the complex dynamics between traffickers and anti-trafficking stakeholders (i.e., interdictors) by capturing how an interdictor's actions impact the traffickers' ability to operate, allowing us to explore strategic interdictions that maximize detection. In this study, we assume traffickers aim to maximize the probability of operating the network undetected, while interdictor(s) seek to minimize the likelihood that trafficking operations remain undetected by implementing interventions throughout the network. As such, we present a bi-level network interdiction model that merges the min-max evasion and min-max flow network interdiction models [137, 150].

As is common in network interdiction models, we assume that the anti-trafficking interdictors know how the traffickers react to the interventions and take this knowledge into account when deciding which interventions to implement. Additionally, traffickers are aware of the interventions that have been implemented and use this information to strategically determine how much they want to use each arc in the network to continue their trafficking operations while minimizing their chance of detection.

Let $G' = (N', A')$ represent the network on which this occurs, where N' represents the set of nodes and A' represents the set of arcs. In addition to the nodes of the labor trafficking supply network illustrated in Figure 3.1, N' also includes a source node s and sink node t such that trafficking operations flow from s to t along the arcs. The structure of, and flow through, the network illustrates the ways trafficking operations in the U.S. agricultural industry recruit the workers they exploit.

In this strategic game, the interdictors initiate action by selecting interventions from a set D to improve detection within the network. The formulation we use can account for interventions that occur at nodes (e.g., improved housing inspections) or along arcs (e.g,. improving detection of illegal fees imposed upon migrant workers on a work visa) within the network. Operationally, we allow this by using a node-expansion technique that splits each node $i \in N' \setminus \{s, t\}$ into two and creates an arc between them to adapt the original network (i.e., G') in which interdictions occur on both nodes and arcs to a solely arc-based interdiction network, denoted $G = (N, A)$. [167] proves the equivalency.

The presence of multiple interdictors operating in the same area of a network can lead to challenges both in reality and in the mathematical modeling. For example, when multiple anti-trafficking stakeholders intervene in the same area of the network, the impact of their efforts may be enhanced or reduced by the presence of the other and depends on the level of coordination and collaboration (if any) between the stakeholders. As a result, the vast majority of network interdiction models only consider a single interdictor. To circumvent the modeling challenges that come with incorporating the decisions of multiple interdictors, we include "collaborative" interventions within the set D. For example, if interdictor A and interdictor B can use a particular detection tactic to intervene on arc (i, j) independently or collaboratively, we add three interventions to the set D: one for interdictor A using the detection tactic to intervene on (i, j), one for interdictor B using the detection tactic to intervene on (i, j), and one for interdictor A and B collaborating to use the detection tactic to intervene on (i, j). This necessitates adding the assumption that at most one intervention from D is chosen to be implemented on each arc.

Within the current baseline environment in which no new interventions are implemented, traffickers already have some risk of being detected. We denote p_{ij} as the liklihood that traffickers currently pass undetected through arc $(i, j) \in A$ if no new interdiction happens on that arc. However, each intervention the interdictors decide to implement will affect the traffickers' chance of evading detection.

Denote the decision of whether or not to implement intervention $d \in D$ by the binary variable X^d that takes the value of 1 if intervention d is implemented and 0 if it is not. Because an intervention can affect multiple arcs, we use the binary parameter v_{ij}^d to indicate whether intervention d affects arc $(i, j) \in A$ if it is implemented. Then, we can also introduce two auxiliary variables: let X_{ij}^d be a binary variable that takes the value of 1 if intervention $d \in D$ is implemented and affects arc (i, j), and let X be the vector containing the X_{ij}^d decision variables $\forall (i, j) \in A, d \in D$.

The effectiveness of each intervention implemented is uncertain. We capture this by incorporating stochasticity into the model and taking a scenario-based approach. That is, once the interdictors decide the subset of interventions to implement, the impact of those interventions on the traffickers' ability to evade detection is realized. While, in reality, the impact of each individual intervention comes from a continuous distribution, for tractability, we consider discrete levels of intervention impact, denoted by the set F. In our case study, we assume two levels of intervention effectiveness for each intervention: low and high impact. We let q_{ij}^{df}, where $q_{ij}^{df} \leq p_{ij}$, represent the probability of traffickers evading detection along arc $(i, j) \in A$ if the realized impact of taking intervention $d \in D$ is $f \in F$. The corresponding probability that impact f occurs is denoted θ_{ij}^{df}. We assume that if an intervention affects multiple arcs, the realized level of impact of the intervention is the same for all arcs (e.g., if a disruption affects two arcs, then they will both either realize a low or both realize a high impact from that disruption; one will not be low and the other high). Relaxing this assumption is left for future work.

The collective information regarding the realized impact of all interventions taken is defined as a scenario ω and the set of all scenarios is $\Omega(X)$. For example, if the interdictors decide to implement two interventions on different arcs, then $\Omega(X)$ would contain four elements, representing the situation in which both realized low impact, one realized low impact and the other high impact, vice versa, and both realized high impact. More generally, because the impacts are categorized as either high or low, the total number of possible scenarios is $2^{\sum_{d \in D} X^d}$. Thus, $\Omega(X)$, is decision-dependent because which interdictions determine the size and elements of $\Omega(X)$. Assuming independence between interventions in different parts of the network, we can then calculate the probability, $\phi^\omega \in \Omega(X)$, that scenario ω occurs. A detailed description of how we do this is available in Appendix B.

After the interdictors decide on their intervention strategy, the traffickers observe the intervention and the the impact of the intervention, and then proceed to operate on the network to maximize their chances of evading detection. Two decision variables represent the flow traffickers place on arcs in scenario $\omega \in \Omega(X)$: Y_{ij}^{ω} corresponds to flow on an arc $(i,j) \in A$ that hasn't been intervened upon and $Z_{ij}^{d\omega}$ corresponds to flow in the case where intervention d has been implemented on arc (i,j). This allows the model to use the associated baseline or updated evasion probability correctly. Hence, we add constraints to ensure Y_{ij}^{ω} and $Z_{ij}^{d\omega}$ are not simultaneously positive.

Different from a traditional min-max evasion model, we also restrict the flow by arc capacities u_{ij} to ensure that the flow through the network occurs along multiple paths (similar to a max flow model) rather than a single path (as is typical in evasion models). This is necessary because traffickers do not just choose a single recruitment, movement, exploitation, etc. tactic and apply it to all of their victims. Instead, traffickers employ a variety of approaches, even within the same trafficking operation.

3.4.2 Model formulation

Here we summarize the notation for our bi-level min-max evasion network interdiction model, followed by the model formulation.

Sets and indices

N Set of nodes, where $s \in N$ is the source node and $t \in N$ is the sink node

A Set of arcs

D Set of interventions

F Set of interventions' impact (e.g., low and high)

$\Omega(X)$ Set of all possible scenarios resulting from interdiction decision X

Input parameters

v_{ij}^{d} Takes value 1 if intervention $d \in D$ affects arc $(i, j) \in A$; 0 otherwise

p_{ij} Probability trafficking occurs undetected along arc $(i, j) \in A$ if no intervention is taken

q_{ij}^{df} Probability trafficking occurs undetected along arc $(i, j) \in A$ if intervention $d \in D$ is implemented and realizes an impact of $f \in F$

$q_{ij}^{d\omega}$ $\in \{q_{ij}^{df} | f \in F\}$Realization of the probability that trafficking occurs undetected along arc $(i, j) \in A$ in scenario $\omega \in \Omega(X)$ if intervention $d \in D$ is implemented and realizes an impact of $f \in F$

u_{ij} Capacity of arc $(i, j) \in A$

b Total intervention implementation budget

c^{d} Cost to implement intervention $d \in D$

θ_{ij}^{df} Probability that intervention $d \in D$ on arc $(i, j) \in A$ has impact $f \in F$

ϕ^{ω} Probability scenario $\omega \in \Omega(X)$ occurs

Iterdictors' decision variables

X_{ij}^{d} Binary variable that takes value 1 if intervention $d \in D$ is taken on arc $(i, j) \in A$, 0 otherwise

X^{d} Binary variable that takes value 1 if intervention $d \in D$ is taken anywhere in the network, 0 otherwise

X Vector containing the binary variables X_{ij}^{d} $\forall (i, j) \in A$, $d \in D$

Trafficker decision variables

Y_{ij}^{ω} Positive if no intervention was taken on arc $(i, j) \in A$ and traffickers decide to continue operations on arc (i, j) in scenario $\omega \in \Omega(X)$

$Z_{ij}^{d\omega}$ Positive if traffickers decide to continue operations on arc (i, j) in scenario $\omega \in \Omega(X)$ after intervention $d \in D$ was implemented on arc (i, j)

Z^{ω} Vector containing the variables $Z_{ij}^{d\omega} \forall (i, j) \in A, d \in D$

R^{ω} Auxiliary variable representing the flow that reaches the sink node $t \in N$ in scenario $\omega \in \Omega(X)$

Using this notation, the interdictors' problem becomes:

Interdictor's Problem:

$$Min_X \sum_{\omega \in \Omega} \phi^{\omega} \hat{R}^{\omega}(X) \tag{3.1}$$

S.t.:

$$\sum_{d \in D} c^d X^d \leq b \tag{3.2}$$

$$X^d \geq X_{ij}^d \qquad \forall (i, j) \in A, d \in D \tag{3.3}$$

$$X_{ij}^d \leq v_{ij}^d \qquad \forall (i, j) \in A, d \in D \tag{3.4}$$

$$\sum_{d \in D} X_{ij}^d \leq 1 \qquad \forall (i, j) \in A \tag{3.5}$$

$$X_{ij}^d, X^d \in \{0, 1\} \qquad \forall (i, j) \in A, d \in D \tag{3.6}$$

The interdictors' primary goal to minimize the expected maximum probability that trafficking operations will evade detection is reflected in objective function (3.1). They must make these decisions considering that each intervention d has a cost c^d and that they must ensure the total cost of their interventions does not exceed their available budget, b. (i.e., constraint 3.2). Together constraints (3.3) and (3.4) ensure that an intervention only affects arc (i, j) if the intervention is taken and is relevant to that arc. Constraints (3.5) ensure at most one intervention occurs on each arc. Constraints (3.6) impose binary restrictions on the interdiction decision variables.

This bi-level formulation assumes that the decisions taken (i.e., the interventions implemented) by the interdictors are known to the traffickers. Hence, given a set of interdictions implemented, we can determine the traffickers' response for each possible realization of the effectiveness of the interventions (i.e., each $\omega \in \Omega(X)$) through the following:

Trafficker's Problem

$$\hat{R}^{\omega}(X) = \quad Max_{Y^{\omega},Z^{\omega},R^{\omega}} R^{\omega} \tag{3.7}$$

S.t.:

$$\sum_{(s,j)\in FS(s)} (Y_{sj}^{\omega} + \sum_{d\in D} Z_{sj}^{d\omega}) = 1 \tag{3.8}$$

$$\sum_{(i,j)\in FS(i)} (Y_{ij}^{\omega} + \sum_{d\in D} Z_{ij}^{d\omega}) = \sum_{(j,i)\in RS(i)} (p_{ji} Y_{ji}^{\omega} + \sum_{d\in D} q_{ji}^{d\omega} Z_{ji}^{d\omega}) \quad \forall i \in N \backslash \{s,t\} \tag{3.9}$$

$$R^{\omega} = \sum_{(j,t)\in RS(t)} (p_{jt} Y_{jt}^{\omega} + \sum_{d\in D} q_{jt}^{d\omega} Z_{jt}^{d\omega}) \tag{3.10}$$

$$Y_{ij}^{\omega} \leq (1 - \sum_{d\in D} X_{ij}^{d}) * u_{ij} \quad \forall (i,j) \in A \tag{3.11}$$

$$Z_{ij}^{d\omega} \leq X_{ij}^{d} * u_{ij} \quad \forall (i,j) \in A, d \in D \tag{3.12}$$

$$Y_{ij}^{\omega} \geq 0 \quad \forall (i,j) \in A \tag{3.13}$$

$$Z_{ij}^{d\omega} \geq 0 \quad \forall (i,j) \in A, d \in D \tag{3.14}$$

$$R^{\omega} \geq 0 \tag{3.15}$$

In the trafficker's model, the objective function (3.7) captures the trafficking operations' aim to maximize their probability of evading detection. Constraint (3.8) ensures 100% of the trafficking flow begins at the start node s, allowing traffickers to navigate the network from this point strategically. Constraint (3.9) is the flow balance constraint, which states that the flow into the node must equal the flow out of the node, adjusted by the probability of detection. That is, because the flow in this model represents the traffickers' cumulative probability of evading detection, as the flow moves through the echelon there are more opportunities for detection. The flow through the network captures this cumulative evasion probability. R^{ω} in constraint (3.10) defines the flow that reaches the sink node $t \in N$ in scenario ω, thus representing the overall probability of evading detection. If an intervention is implemented on an arc $(i,j) \in A$, the trafficker loses access to the original, un-intervened version of this arc (3.11). Furthermore, constraints (3.12) state that the trafficker can only use the arc $(i,j) \in A$ associated with intervention $d \in D$ if intervention $d \in D$ has been implemented. The remaining constraints are non-negativity constraints on the flow.

3.5 Data and Interventions

Data related to human trafficking operations and interventions is notoriously difficult to obtain due to the illegal and illicit nature of trafficking, conflation with other types of labor exploitation and unethical behaviors, the lack of transparency within supply chains, and limited intervention evaluation studies [168, 152]. As such, in this section, we explain how we decided upon the input data used to run the model and generate high-level insights from the bilevel network interdiction model. To address the lack of comprehensive data, we triangulated data from multiple sources, including expert knowledge (such as that from trafficking survivors, legal advocates, labor rights organizations, law enforcement, prosecutors, government officials, and academics), extant literature (including peer-reviewed journals, government reports, and media), and federally prosecuted human trafficking agricultural labor trafficking cases within the U.S. (see our work in [164, 128] to read more about these cases and the data collected). We also perform sensitivity analysis on these data to help address the uncertainty in precision. All of the input data is provided in the Appendix B.

Evasion Probability Pre-Interdiction: Our model is designed to provide insights into the impact of implementing additional interventions to improve labor trafficking detection while simultaneously acknowledging current ongoing efforts. That is, our model assumes that even if no new interventions are implemented, some trafficking will still be detected from ongoing efforts. This is reflected in the model by the p_{ij} parameters.

After a thorough search of the literature, evaluation study reports, and related datasets, we concluded that this type of data does not currently exist. We, therefore, implemented an expert opinion elicitation method—a common approach used in situations where data is insufficient [169, 170, 171]—and then used the elicited opinions to estimate the p_{ij} probabilities.

Specifically, we asked human trafficking scholars from a variety of disciplines to provide their thoughts on the lower limit, upper limit, best estimate, and their levels of certainty regarding the likelihood of trafficking activities currently going undetected at each point in the labor trafficking network. We then encoded this elicited data in a Beta distribution to model the uncertainty and variability of evasion using the `betaExpert` function within the R prevalence package [172, 173]. The Beta distribution, which is the conjugate distribution for Bernoulli sampling, typically describes the distribution of a proportion or a probability. In our model, this distribution is employed to model the evasion probabilities or detection rates, effectively capturing expert opinions on these probabilities [174]. Additionally, the Beta distribution's flexibility is evident as it can adapt to various shapes depending on its parameters, alpha (α) and beta (β). This adaptability is valuable where the elicited data may be skewed, allowing for more accurate modeling under such conditions [175, 171]. The `betaExpert` output provides the α and β parameters of beta distributions, and we selected the median of the resulting beta distributions to represent the estimated evasion probabilities for each arc within the network.

Capacities: The arc capacities within the network function to ensure that, in the absence of any interventions, the flow through the network aligns with the current fraction of trafficking operations that use each part of the trafficking network. However, although there have been studies that explore human trafficking within the U.S. agricultural sector (e.g., [120, 176]), much of the information about the percentage of trafficking operations that use each of the recruitment methods, legal status, movement options, housing options, and exploitation schemes we consider is still an open question. We, therefore, used logic rules and built assumptions based on the extant literature.

Potential Interventions: Based on the multiple aforementioned sources of information, we developed a list of potential interventions to consider within the network interdiction model. We intentionally chose interventions that affected different echelons and arcs within the network and interventions that could be enacted by different stakeholders to include a sense of diversity within the interventions considered. We specifically focused on interventions within the prevue of the U.S. DOL and/or the U.S. DHS. Ultimately, we chose 12 interventions to consider, as shown in Table 3.1, motivated by the current challenges in detecting labor trafficking. These include insufficient inspection routines that could identify violations more effectively [127, 177], the critical need to improve information sharing among agencies [178, 179], the need to strengthen relationships between workers and government actors—particularly non-citizens—who often do not report labor abuses due to fear of deportation and distrust of authorities [180], improving access to multilingual resources and training for workers to understand their rights and job details [181, 182], and a lack of training for law enforcement personnel [183, 184, 185], among others. Note that some interventions focus specifically on certain populations (e.g., H-2A workers or non-citizens) whereas others are broader in scope.

Nine of the interventions can be implemented by a single agency, and three focus on interventions that require collaboration between DOL and DHS. We stress that there are certainly more stakeholders that can (and should) intervene to address labor trafficking within the U.S. agricultural sector and many more ways that current efforts to address trafficking can be improved. We do not claim to consider all possible interventions or actors, as it is not practical. Instead, we aim to show a proof-of-concept of the insights that could be obtained from a min-max evasion network

Table 3.1: Twelve interventions are considered in our case study

ID	Interdictor	Population Affected	Definition
d1	DOL	All	**Improve interview skills training for detecting recruitment violations:** provide regular training sessions for staff to develop skills related to identifying signs of fraud, force, coercion, and fee violations during interviewing applicants, emphasizing recent tactics used by traffickers or other employers performing illegal actions.
d2	DOL	All	**Fee violations identification:** Refine the interview skills and document analysis skills of DOL staff to identify fee manipulation and document violations in recruitment fee practices.
d3	DOL	All	**Strengthening worker-DOL trust:** enhance trust and communication between farm workers and DOL to increase workers' trust in reporting labor violations and trafficking.
d4	DOL	All	**Increase and improve DOL inspections:** increase DOL inspector capacity to ensure all worksites/labor camps are inspected regularly and establish a streamlined method for inspectors to confidentially interview a representative sample of workers, confirming the actual conditions against reported claims.
d5	DOL	H-2A Workers	**Multilingual housing and work conditions database for H-2A workers:** develop an online database, accessible in multiple languages, listing DOL-verified housing options specifically for H-2A workers with a reporting feature for housing and labor concerns. Share this resource with workers during and after the H-2A application process.
d6	DHS	H-2A Workers	**Multilingual database and outreach for safe H-2A recruitment:** develop a public database, accessible in multiple languages, listing verified H-2A labor recruiters and agencies, complemented by an outreach campaign to educate workers in their hometowns on using the database for verifying recruiters and reporting suspicious recruiters.
d7	DHS	All	**Strengthening official border screening for labor trafficking:** bolster the screening processes and resource availability to improve the identification and assistance of potential labor trafficking victims at all official border crossing points (sea, land, air).
d8	DHS	Farms that hire H-2A workers	**Enhanced DHS inspections:** increase DHS inspector capacity to ensure all H-2A visa worksites/labor camps are inspected regularly and establish a streamlined method for inspectors to confidentially interview a representative sample of workers, confirming the actual conditions against reported claims.
d9	DHS	All	**Unofficial crossing screening and worker protection training:** provide specialized training for DHS-CBP staff related to screening for labor trafficking at unofficial border crossings, with a focus on labor trafficking indicators and understanding the person's motivations for crossing at an unofficial border crossing so that appropriate post-identification resources and interventions can be pursued.
d10	DOL and DHS	Non-U.S. Citizens	**Improve DHS relations with non-citizens:** implement new policies and practices at DHS related to how DHS interacts with non-citizen workers who disclose workplace exploitation to DOL. Specifically, when DOL encounters a non-citizen worker being exploited, DOL should work with DHS to ensure the victim is not deported but rather that victim-based immigration benefits and temporary status are provided while ensuring the victim's basic needs are met after getting out of the exploitative situation.
d11	DOL and DHS	All	**DHS border monitoring informs DOL follow-up:** improve communications between DHS and DOL so that if DHS uncovers potential labor trafficking victims during the border monitoring process, DOL performs enhanced inspections and investigations at the affiliated worksite.
d12	DOL and DHS	All	**Improve information sharing:** improve information sharing between DOL and DHS regarding workplace and labor camp inspections, investigations, and violations.

interdiction model that considers a range of interventions and interdicting agents.

Each of the proposed interventions affects one or two echelons, and some interventions may not affect all arcs within an echelon (Figure 3.2). For example, intervention d2 focuses on improving detection of unlawful recruitment fee practices, and thus only affects the arcs within the recruitment echelon that involve exploitative fees. As shown in the heatmap, d2 impacts 8 of the 15 arcs within the recruitment echelon.Interventions d4, d5, and d8 within the housing echelon, and d7 and d9 in the movement echelon also impact less than 100% of the arcs in the echelon. Three interventions affect two echelons: d4, d8 and d12. All other interventions affect only one echelon. Intervention d12 also stands out as an intervention that has particularly large coverage within the network; not only does it impact both the housing and exploitation echelons, it also affects all arcs within both of these echelons and is the intervention that affects the largest number of arcs (i.e., 18 arcs). On the other hand, d5 and d9 stand out as interventions that only affect one arc within the network. Additionally, Figure 3.2 reveals that the housing and exploitation echelons are extensively covered by the interventions considered, with four interventions impacting the housing echelon and six targeting the exploitation echelon. While no interventions are considered that affect the status echelon, some of the interventions do focus specifically on certain populations (e.g., H-2A workers or non-citizens) whereas others are broader in scope (Table 3.1). We describe more about how we incorporated this below.

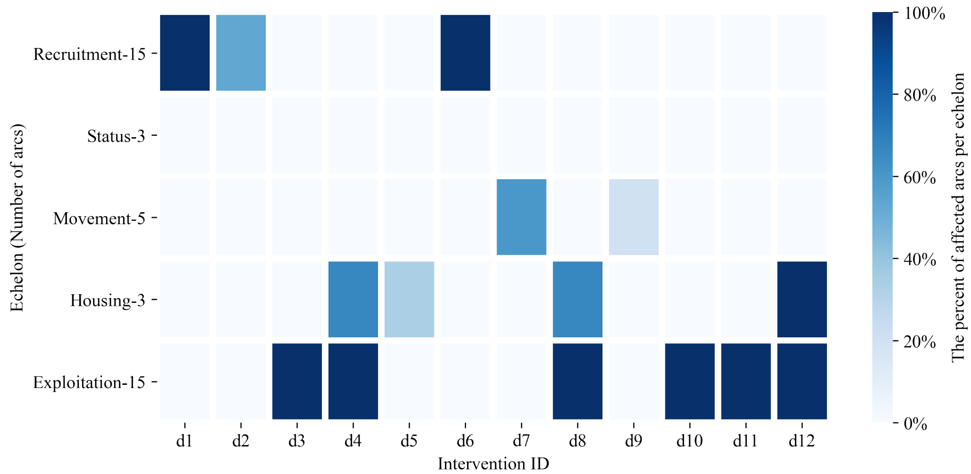


Figure 3.2: The percentage of arcs within an echelon impacted by each intervention differs.

Post-Intervention Evasion Probability: After an intervention occurs at a specific arc, the evasion probability decreases to the post-intervention evasion probability $q_{ij}^{d\omega}$ with probability $\theta_{ij}^{d\omega}$. In our case study we consider two potential levels of realized impact for each arc and intervention combination: low impact or high impact. Due to the lack of precise data for either of these parameters, we implemented an approach that translates expert opinions into quantifiable probabilities [186] and co-creates logic assumptions with human trafficking domain experts. The outcome of this process resulted in assuming that the maximum reduction in evasion probability, as compared to the pre-intervention evasion probability is 10% for low impact and 20% for high impact realizations, and the minimum reduction rate in evasion probability is 1% and 10% for low and high impact scenarios, respectively. These rates are adjustable and can be adapted in future analyses to reflect the specifics of different interventions and their contexts. The post-intervention evasion probabilities $q_{ij}^{d\omega}$ were then derived by applying the formula

$q_{ij}^{d\omega} = (1 - \text{reduction rate}) \times p_{ij}$ for each arc and intervention. Although the reduction rate was assumed to be consistent across all arcs for a given intervention, it varied depending on the nature of the intervention itself. Additionally, because interventions d5, d6, d8, and d10 relate to specific specific populations (meaning only a portion of the flow along these arcs is impacted by the interventions, see Table 3.1), we adjusted the values of $q_{ij}^{d\omega}$ based on the proportion of workers or farms these interventions cover, ensuring that our model accurately reflects the focused impact of these strategies. This methodological approach ensures a systematic estimation of intervention impacts across the network. The resulting post-interdiction evasion probabilities are available in the Online Supplement.

Probability of Low or High Impact Realization: The expert opinion elicitation approach mentioned above was also used to identify the $\theta_{ij}^{d\omega}$ values. Specifically, we asked the experts to state whether an intervention was ”highly unlikely”, ”unlikely”, ”about even (50-50)”, ”likely”, or ”highly likely” to result in the high-impact realization. We converted these qualitative assessments into numerical probabilities using the mode of the distributions from [187] which mapped how people commonly interpret subjective probabilities. Specifically we assumed the qualitative responses indicated a 10%, 30%, 50%, 70%, and 90%, chance of the high impact scenario occurring, respectively. After estimating these parameter values for all interventions and their corresponding arcs, we separately calculated the average $\theta_{ij}^{d\omega}$ for all impacted arcs per intervention for low and high impact scenarios.

3.6 Result

Our primary aim is to explore how interventions affect the likelihood of detecting trafficking operations. Herein, we provide insights related to how the percentage of arcs and echelons affected by interventions and changes to the number of simultaneously implemented interventions affect the optimal intervention strategy and corresponding impact on the cumulative evasion probability.

The model was coded in Python 3.8.5 and solved using Gurobi 9.1.2 [188, 189]. Due to the decision-dependent scenario probabilities, traditional methods of solving bilevel network interdiction problems, such as Benders Decomposition [190], are not suitable for the model. Other researchers have addressed the challenge of decision-dependent uncertainty by implementing Genetic Algorithms (GA) [133]. However, GA does not guarantee optimality. In our case, the number of potential interventions and resulting scenarios enables us to perform an exhaustive search in a manageable amount of time. This approach directly evaluates every feasible combination of interventions, eliminating the need for iterative sampling typically required in traditional GA applications. An added benefit to an exhaustive search is that it enables us to explore how any decision that the anti-trafficking interdictors may make will perform. This is especially insightful because it facilitates discussion among anti-trafficking decision makers regarding why sub-optimal intervention strategies (according to the model) may be preferred in practice (e.g., externalities that the model doesn't consider). However, the model could also be solved using a GA if a larger number of interventions or scenarios were to be considered.

Because of the uncertainty caused by the data limitations, we present a robust sensitivity analysis and focus on the general insights that can be obtained through our min-max evasion network interdiction model. We note that given an objective function value for a solution to the trafficker's maximizing evasion problem, we can easily calculate the solution's corresponding probability of being detected (i.e., Probability of Detection = 1 – probability of evasion). Throughout this section, we present results about the relative increase in detection from implementing interventions from set D as compared to the baseline situation in which no new interventions are implemented. This allows us to compare how implementing interventions from D improves the the overall detection rate compared to the current ability to detect trafficking.

The results indicate that in the absence of a budget constraint (i.e., constraints (3.2) are removed), simultaneously implementing four interventions, spanning the recruitment, movement, housing, and exploitation echelons, provides the greatest impact on increasing the trafficking detection rate throughout the network (a 72% increase compared to the baseline by implementing interventions d1, d7, d9, and d12). However, there are often reasons why implementing multiple interventions simultaneously is not practical in reality. Therefore, we also explored the optimal solutions to the problem when a limit to the number of simultaneous interventions is present (i.e., constraints (3.2) are present). Table 3.2 shows that if at most one intervention can be implemented, d12 provides the greatest impact on detecting trafficking operations. In fact, intervention d12 appears in the optimal solution regardless of whether a maximum of 1, 2, 3, or 4 interventions is allowed. We note that although feasible solutions do exist in which 5 simultaneous interventions occur, they all perform worse than the case of even just implementing one intervention; the best-performing solution with 5 simultaneous interventions results in a 54% increase in detection compared to baseline, whereas simply implementing d12 results in a 61% increase in detection compared to baseline). Intervention d12 is not included in the optimal set for scenarios with five simultaneous interventions because, due to our model's constraint that only one intervention can happen at each arc, there are no feasible combinations of five simultaneous interventions that include d12. Moreover, no feasible solutions exist that include six simultaneously implemented interventions. Overall, there are 207 feasible solutions to the problem when the budget constraint is not considered.

Table 3.2: The optimal solutions when implementing a different number of interventions simultaneously differs.

Number of interventions	**Optimal solution interventions**	**Increase in detection rate**	**Echelons affected**
1	d12	61%	Housing, Exploitation
2	d1, d12	67%	Recruitment, Housing, Exploitation
3	d1, d9, d12	71%	Recruitment, Movement, Housing, Exploitation
4	d1, d7, d9, d12	72%	Recruitment, Movement, Housing, Exploitation
5	d1, d4, d5, d7, d9	54%	Recruitment, Movement, Housing, Exploitation

The notable presence of d12 in these optimal solutions prompts us to investigate whether d12 is present in all near-optimal solutions and whether any other sets of interventions perform similarly well. To do this, we explored how each of the 207 feasible solutions perform as compared to the baseline case by classifying the solutions using K-means clustering (see Figure 3.3), which is suitable for clustering numeric data like detection rates [191]. We determined the number of clusters using the elbow and silhouette methods [192, 193]. This grouped the solutions into four distinct clusters (minimal, low, moderate, and high impact) based on the increase in overall detection likeliness they provide. Figure 3.3 illustrates the distribution of the feasible interdiction decisions according to the number of interventions implemented and the corresponding increase in the overall detection likelihood. Of the 207 feasible solutions, 28.5% are classified as minimal impact, 47.34% are classified as low impact, 16.43% are classified as moderate impact, and 7.73% are classified as high impact. Notably, the interventions that include d12 are marked by “X” symbol, highlighting its recurring presence in all of the high impact solutions. This is unsurprising based on d12’s favorable disruption impact parameters (i.e., q_{ij}^{df} and θ_{ij}^{df}) compared to other interventions and given that affects many arcs within two echelons such as housing and exploitation.

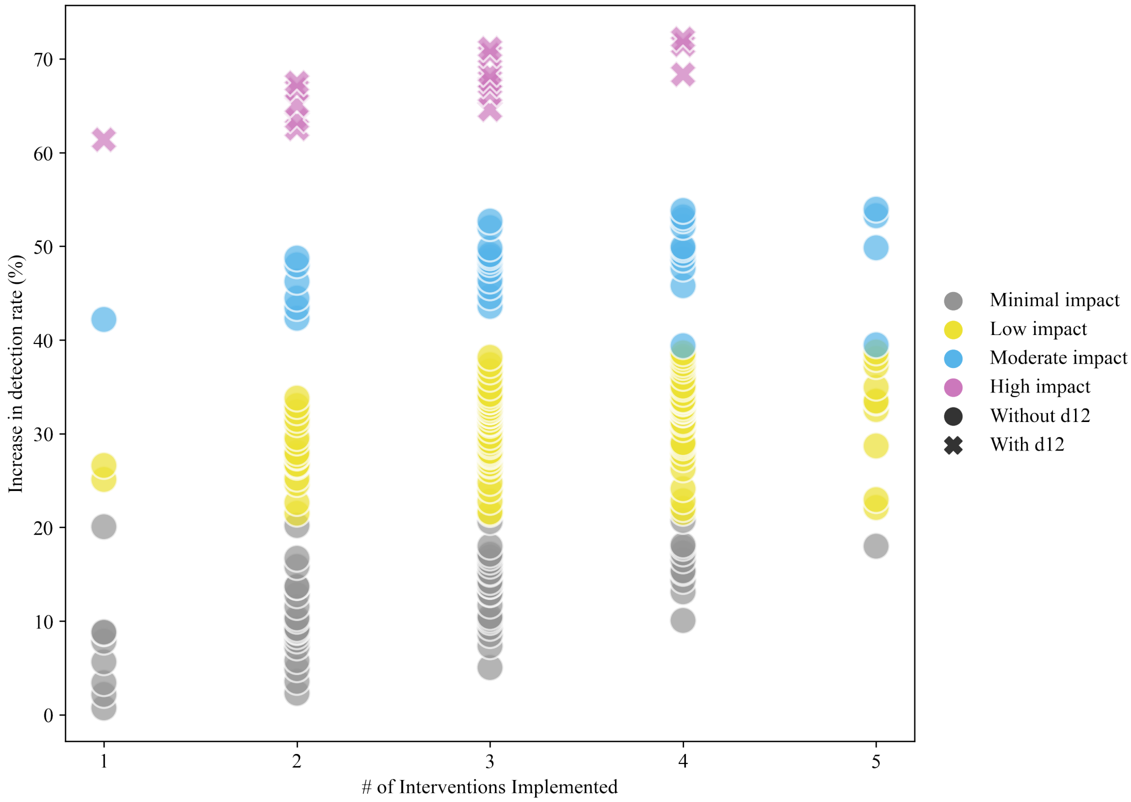


Figure 3.3: A k-means clustering approach classified the overall detection likelihood of the 207 feasible solutions into four distinct clusters: minimal, low, moderate, and high impact.

An important insight from Figure 3.3 is that multiple solutions are nearly as effective as the optimal solution (i.e., d1, d7, d9, and d12 implemented simultaneously). For instance, two solutions ({d2, d7, d9, d12} and {d1, d9, d12}) fall within one percentage point of the optimal overall detection likelihood. Although all three of these solutions involve sets of interventions that effectively increase the overall detection rate across similar echelons, the optimal solution impacts a greater number of arcs throughout the network. Other observations include that intervention d4 is particularly prevalent within the moderate impact group, appearing in almost 94% of the moderate impact solutions. Additionally, five feasible solutions provide a 2% or less improvement to the baseline detection likelihood.

To explore how the number of arcs and echelons affected by a set of interventions impacts the overall disruption likelihood, we plot each solution against the number of arcs and echelons impacted for each of the four clusters (see Figure 3.4). The solutions within the minimal impact cluster affect anywhere between one arc in one echelon to 37 arcs across four echelons. For instance, the solution {d5, d6, d7, d8 and d9} in this cluster impacted fifteen arcs in recruitment, four arcs in movement, three arcs in housing, and fifteen arcs in exploitation.

A distinction between the minimal solution cluster and the other clusters is that all the non-minimal solutions affect at least fifteen arcs in the network, with the low, moderate, and high impact groups influencing at least 15, 17, and 18 arcs, respectively. Additionally, all solutions classified into moderate and high-impact clusters affect at least two echelons in the network. For example, solution {d7 and d12} in the high-impact cluster impacted three echelons and 21 arcs, including three arcs in movement, three arcs in housing, and fifteen arcs in exploitation.

These observations suggest that solutions with broader coverage do not necessarily result in a higher detection rate of labor trafficking, even though they enhance detection across more arcs within an echelon and impact multiple echelons. This emphasizes that other factors, such as the amount by which an intervention improves detection (i.e., reduces evasion) along individual arcs, also influence the effect of intervention strategies.

3.6.1 Sensitivity analysis

As previously mentioned, the impact an intervention (or set of interventions) has on improving the overall likelihood of detecting human trafficking throughout the network is influenced by multiple factors, including the network structure, the number of arcs and echelons the interventions affect, and the intervention's local effect of increasing detection on the arcs it directly affects. We present two sensitivity analyses to explore how these factors influence the solution's performance.

First, we explore the impact of the number of echelons and the percentage of arcs within an echelon affected by an intervention. We do this with the twelve aforementioned interventions but change their input data such that the only way in which they differ is in which parts of the network they impact (i.e., we set the resulting evasion probability q_{ij}^{df} and probability of achieving an impact level of $f \in F$ post-implementation θ_{ij}^{df} to the same value $\forall (i,j) \in A, d \in D$). As a result, some of

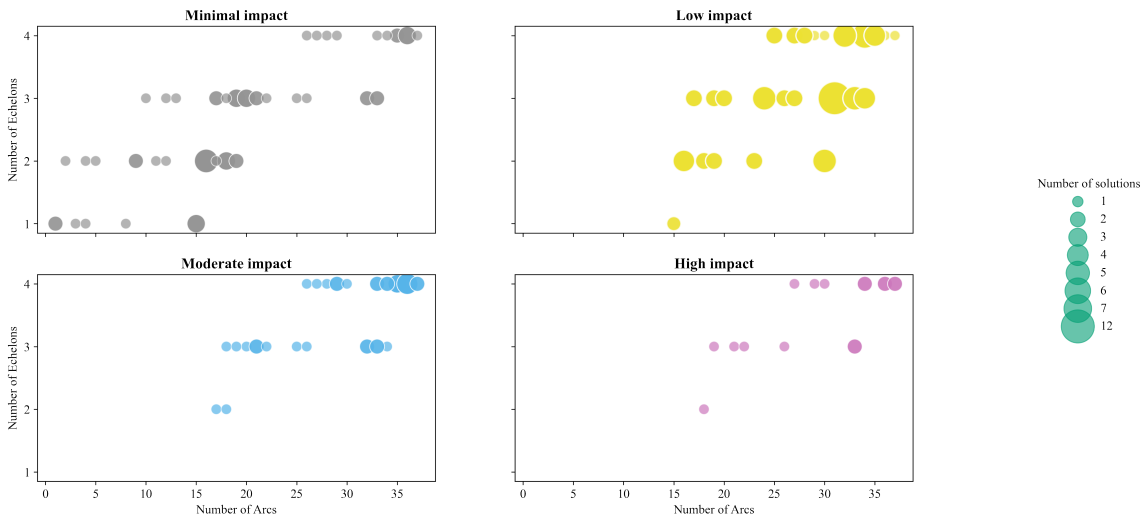


Figure 3.4: The 207 feasible solutions are categorized by the number of echelons and arcs affected, grouped by the clustered impact each solution has on the overall likelihood of detecting trafficking.

the interventions perform identically in the model because they affect the exact same arcs (e.g., d1 and d6; d4 and d8; d3, d10, and d11). Thus, while there are still technically 207 feasible solutions, there are at most 71 feasible solutions that perform differently within the model for this analysis.

The results indicate that the spread of detection rates has narrowed, leading our clustering approach to categorize the outcomes into two distinct groups: low and high. The low impact cluster contains 40% of the 207 feasible solutions whereas the high impact cluster contains 60% of the feasible solutions (see Figure 3.5). High impact intervention strategies affect at least three echelons and eighteen arcs within the network. Notably, 39.5% of these sets include collaborative interventions, such as d10, d11, and d12. In contrast, the maximum number of arcs influenced by the low impact groups is thirty.

Despite having the same input parameter values as the other interventions, d12 still stands out as an impactful intervention; 94% of the interventions that include d12 fall into the high impact category. This may be because it is the only intervention that affects all of the arcs in two echelons; the two other interventions that affect multiple echelons affect all of the arcs in one echelon but only some of the arcs in the second echelon (i.e., d4 and d8 both affect 100% of the exploitation arcs but only 66.7% of the housing arcs, see Figure 3.2).

In this consistent input data analysis, the results indicate that the two most effective combinations of interventions to implement are {d1, d7, d9, d12} and {d6, d7, d9, d12}. Interventions d1 and d6 affect the same arcs, which is why these multiple optimal solutions occur. These two solutions have interventions that affect four of the echelons and 37 arcs within the network (of 41 arcs) that can be impacted by the set of 12 interventions considered. It should be noted that numerous sets within the high impact group do not include d12, indicating a wider variety of effective interventions in the consistent input data analysis. For example, the next set of effective solutions are {d5, d6, d7, d8, d9}, {d1, d5, d7, d8, d9}, {d1, d4, d5, d7, d9} and {d4, d5, d6, d7, d9}.

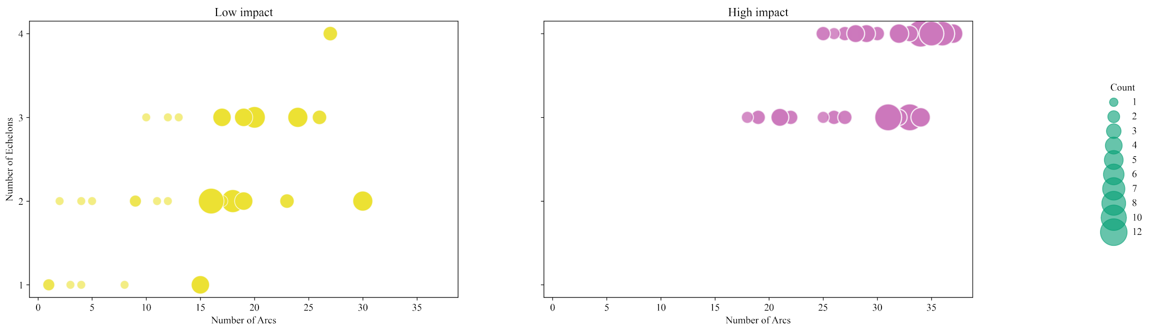


Figure 3.5: The 207 feasible solutions are categorized by the number of echelons and arcs affected, grouped by the clustered impact each solution has on the overall likelihood of detecting trafficking when all of the interventions have the same input data parameters. The only way in which these interventions differ in this analysis is in which arcs and echelons they affect.

Our second sensitivity analysis focuses on understanding how changes in the intervention effectiveness influence the overall detection rate. Specifically, due to its overwhelming presence in the high-impact solution cluster, we explore how changes to the probability that trafficking operations pass through an arc undetected after intervention d12 occurs ($q_{ij}^{d12,f}$) affects its performance. In the original case study, we assumed that if d12 was implemented and realized a high-impact on the affected arcs it would reduce the evasion probability by 20% as compared to the likelihood of traffickers evading detection when no intervention is implemented (i.e. $q_{ij}^{d12,high} = (1 - .2)p_{ij}$). Similarly, a low-impact realization would result in a 10% reduction. For this sensitivity analysis, we varied the post-intervention probabilities $q_{ij}^{d12,f}$ for d12 by considering a range of reductions to the baseline evasion probability p_{ij} for each associated arc. Specifically, the reduction rates for both low-impact and high-impact realizations were varied simultaneously. For example, if the high-impact reduction rate was initially 20% and the low-impact reduction rate was 10%, they were adjusted to 15% and 5%, respectively.

Figure 3.6 shows how reductions to the baseline evasion probability after the implementation of d12 affects whether d12 is classified in the high-impact cluster. It should be noted that in all cases where the baseline evasion probability was reduced, the analysis resulted in three distinct clusters. (Note that the terms ”high-(low-)impact realization” and ”high-(low-)impact solution/cluster” refer to different things. The former refers to the amount of reduction in evasion probability that arcs directly affected by the intervention realize in a scenario, because of the uncertainty in implementation impact. The latter refers to how much a solution, which may include multiple interventions, reduces the overall likelihood of evading detection throughout the whole network and is determined through the k-means clustering). The results show that when the high-impact realization results in at least a 15% reduction in evasion along the impacted arcs as compared to the baseline case (i.e., as long as $q_{ij}^{d12,high} \leq (1 - .15)p_{ij})$, all of the feasible solutions that contain d12 are classified as high-impact solutions in the k-means clustering. We also observed that no solutions that contain d12 are present in the high-impact cluster when the reduction rate is set to 1% for low impact and 10% for high impact.

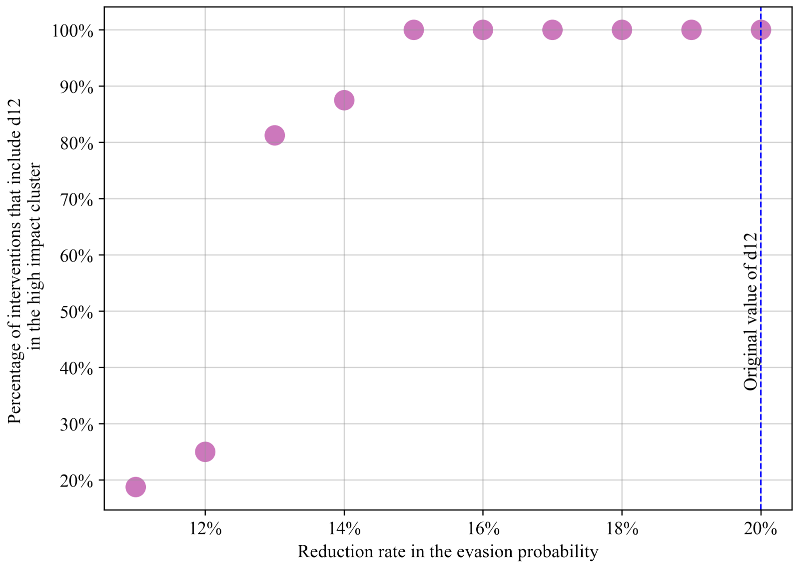


Figure 3.6: Of the solutions that contain d12, the percentage of them that are classified into the high-impact cluster varies as the post-intervention evasion probability for d12 varies. This graph displays the amount by which an intervention would reduce traffickers evasion probability as compared to the non-interdicted upon probability of evasion.

3.7 Conclusion

This paper provides novel insights into the structure of labor trafficking recruitment to exploitation supply chain networks within the U.S. agricultural sector and produces a novel bi-level network interdiction model to enhance the effectiveness of disrupting such networks. This work was undertaken by an interdisciplinary team with expertise in optimization, supply chains, criminology, and human trafficking, and was informed by a detailed analysis of twelve federally prosecuted cases and discussions with multiple stakeholders.

In an illustrative case study, we consider twelve potential anti-trafficking interventions and assess their ability to reduce the likelihood that traffickers will be able to operate throughout the entire network without detection. The scope of the model and network enabled us to evaluate all feasible solutions to this problem using a k-means approach to categorize the feasible solutions into four clusters based on their impact of improving detection. We found that solutions in the cluster that enhances the detection likelihood the most typically included interventions that collectively affected at least two echelons and eighteen arcs. However, our findings indicate that simply affecting more arcs and echelons does not guarantee an effective intervention strategy. The efficacy of interventions also depends critically on how they influence the network structure and their specific disruption impact parameters. These insights allow anti-trafficking stakeholders to make informed decisions, balancing available resources against the potential impact of intervention decisions on enhancing detection rates.

This work is not without its limitations. A key challenge is the lack of detailed data on labor trafficking and interventions. To overcome these data limitations, we synthesized information from the literature and used expert opinion elicitation to convert qualitative assessments into quantitative data, thereby increasing the reliability of our model. Additionally, incorporating the effect of multiple interdictors collaborating and the effect of multiple interventions on the same part of the network poses challenges both in terms of modeling complexity and data to inform these features. We therefore assume that at most one intervention can be implemented per arc, which is in line with assumptions in the extant literature. However, we have plans to relax this assumption in future research. In light of these limitations, our intent is to show a proof of concept for the value of these types of models in anti-human trafficking decision making.

Chapter 4

Mitigating Disruptions in Multi-Echelon Agricultural Supply Chains with Multiple Disruption Sources and Intensities

4.1 Introduction

Effective risk assessment and disruption mitigation are essential for maintaining resilient supply chains, which are critical to global trade, economic stability, and the continuous flow of goods and services [6, 194]. Supply chains are vulnerable to disruptions caused by natural disasters, unexpected regulatory issues, port problems, and strikes [195]. Once a disruption happens, recovery can be costly and time-consuming, with severe disruptions potentially leading to a shutdown of the entire supply chain, resulting in substantial lost sales and business interruptions. The risk facing any industry supply chain depends on its level of exposure to various types of disruptions. In reality, many companies are exposed to both domestic and international disruptions and as the complexity of supply chains increases, the impact of disruptions is less predictable.

The supply chain network developed in this research is particularly suited for long-life agricultural products, such as wheat. To demonstrate the practical application of the optimization model, we conducted a case study focusing on wheat supply chains under disruption scenarios. This multi-echelon supply chain includes grain elevators (as suppliers), milling facilities (as processing plants), and the warehouse. Wheat bushels are harvested from hundreds of farms and sent to grain elevators, where they are collected and distributed to milling facilities for processing. The processed products are sent to warehouses and delivered to customers. By modeling this complex network, the case study illustrates how the optimization model can be applied to mitigate the effects of disruptions in agricultural supply chains, improving overall resilience in the wheat supply chain.

Agricultural supply chains are vital in ensuring food security and economic stability, including three key stages: farming and agricultural inputs, processing and storage, and transportation and distribution. Each of these stages is vulnerable to significant disruptions that can severely impact the overall performance and reliability of the supply chain [196]. From unpredictable weather events and natural disasters to market uncertainty and logistical challenges, agricultural supply chains must constantly adapt to mitigate risks. For example, risk of supplier quality issues [197], supply shortages [198], and the underperformance of logistics providers [199] affect the supply-side dimension, while transportation issues [200] and uncertain demand [201] are some sources of risks of the demand-side dimension. Additionally, the seasonality of agricultural supply chains increase their vulnerability to a variety of disruptions. Depending on the location and season, food supply chains are often impacted by different disruptions, such as Midwestern wetness, which causes significant planting delays through spring and summer and delayed harvest activities due to muddy or snow-covered fields during autumn [202]. As agricultural production is significantly influenced by the environmental conditions, post-disaster recovery—from waste removal to re-planting—can be time consuming [203]. This long-term recovery process complicates efforts to mitigate the impacts of disruptions in agricultural supply chains.

The USDA has reported the need for long-term strategies to enhance the resilience of agricultural supply chains, particularly in response to risks such as aging infrastructure, climate change, and workforce shortages [204]. Stakeholders must prioritize these risks and develop targeted mitigation strategies. Recent research highlights the importance of improving analytical techniques, including the use of two-stage stochastic models, to better design disruption scenarios and guide decision-making [205, 206]. This study aims to address these challenges by leveraging OR methods to optimize resilience, manage disruptions in agricultural supply chains.

In this study, we introduce a two-stage stochastic programming model for multi-echelon agricultural supply chains focused on long-life products, such as wheat, under the influence of both domestic and international disruptions. The model accounts for uncertainty in severity of disruptions, incorporating fractional disruptions that can affect different echelons in the supply chain. In the second stage of the optimization model, different types of disruption scenarios are generated to cover varying severities—categorized as low, medium, and high impact—based on three key factors: random start time of the disruption, random duration of the disruption (recovery time), and the reduction in the capacity of affected facilities. This comprehensive scenario generation allows the model to capture a wide range of potential disruptions, ensuring more effective mitigation strategies across the supply chain's multiple echelons.

The proposed model includes different stages of wheat production, such as grain elevators, milling factories, and warehouses. Given that complex supply chains are often disrupted at multiple echelons, the model reduces the impact of disruptions across these levels (e.g., suppliers and factories), moving beyond the traditional approach that typically focuses on a single echelon. This optimization model determines which suppliers and factories to use during non-disruptive periods, while also incorporating the flexibility to contract with recovery suppliers and factories that supplement production during disruptions.

As such, this study makes the following contributions to the agricultural supply chain disruption mitigation literature: First, it introduces a two-stage stochastic model that generates various disruption scenarios, including low, medium and high-impact, to support long-term decision-making on facility selection and mitigation strategies. This scenario-based approach allows for better evaluation of strategies like multi-sourcing and the use of backup facilities to reduce the impact of disruptions and enhance overall resilience. Second, the model incorporates flexibility in handling both partial and full facility disruptions, where facilities are able to continue operating at reduced capacity during recovery. Throughout the recovery period, the capacity of disrupted facilities gradually increases until full operational capacity is restored. The model also accounts for disruptions affecting both primary and backup facilities, ensuring a comprehensive analysis of the supply chain's vulnerability and recovery process. Lastly, the model uses a multi-period time horizon, which allows for the evaluation of supply chain performance over time, accounting for random disruption start times and the possibility of simultaneous disruptions across multiple echelons with varying levels of severity.

The remainder of this study is organized as follows. Section Literature Review provides an overview of the literature on mitigation strategies for supply chains networks under uncertainty with a particular emphasis on food supply chains. We present the two-stage multi-echelon stochastic optimization model in Section Method. To illustrate the benefit of our model, we introduce a case study of wheat supply chains and present the results in Section Case Study. We conclude with insights and future work in Section Discussion and Conclusion.

4.2 Literature Review

In this section, we position our work within the relevant literature on supply chain networks under disruptions, focusing on models that address agricultural supply chains. We review the broader supply chain disruption literature to identify critical studies that inform our approach. Afterward, we explore the specific OR literature on agricultural supply chains, highlighting the particular vulnerabilities of these networks and existing mitigation strategies.

4.2.1 Mitigation strategies for supply chain networks under uncertainties

Effective risk management has become a critical priority for researchers and industry practitioners in response to global supply chains' increasing challenges and vulnerabilities. The growing complexity of modern supply chains, coupled with the rising frequency of disruptive events—ranging from natural disasters to geopolitical instability—necessitates a combination of proactive and reactive strategies [6, 207, 208]. While proactive measures aim to anticipate and mitigate risks before they occur, reactive approaches remain essential for addressing unforeseen disruptions and minimizing their impact. Since supply chains are exposed to a wide range of disruptions, it is essential to thoroughly understand the severity and frequency of these disruptions to better represent them in supply chain models and design more effective mitigation strategies [207, 209, 210].

OR offers significant advantages in managing supply chain disruptions by enhancing proactive and reactive strategies [194, 211]. The mathematical models and simulations enable the analysis of various disruption scenarios, providing organizations with valuable tools to anticipate risks, mitigate vulnerabilities, and design effective recovery plans [212, 213, 214]. These methods equip supply chains to respond efficiently to unexpected disruptions while building long-term resilience.

Several studies have examined supply chain disruptions using various OR techniques [215, 212, 213, 216, 217, 218, 219, 220]. One study employs a simulation framework for a multi-echelon drug delivery supply chain, allowing only one disruption at a time. The researchers assess the supply chain's performance under different levels of disruption severity, offering insights into the impact of these disruptions on drug availability [212]. Another study expanded the disruption profile by considering disruptions at facilities across all supply chain stages. The researchers focused on analyzing mitigation strategies when disruptions were examined at each stage separately. Multiple strategies were implemented to protect customer service, providing valuable insights into how disruptions at individual points in the network could be effectively mitigated [213, 218]. A two-stage stochastic programming model has been used to evaluate supply chain resilience strategies under high-impact (low-impact) and low-frequency (high-frequency) disruptions. The study examined the effectiveness of backup suppliers, spot purchasing, collaboration, and visibility as mitigation strategies [216]. With the expansion to designing more realistic disruption scenarios, another study expanded the two-stage model to handle multiple concurrent disruptions. In this case, the model also integrated multiple sourcing and safety stocks as mitigation strategies, with a multi-period framework where disrupted facilities were unavailable during disruption periods [217]. Although these studies represent different disruption scenarios and mitigation strategies, our research addresses more complex, realistic scenarios where multiple disruptions occur concurrently across multiple echelons, including both primary and backup facilities. Additionally, we allow disrupted facilities to be either partially operational or fully unavailable during the disruption period, offering a more detailed analysis of recovery and operational continuity in the two-stage stochastic model.

The effectiveness of mitigation strategies in reducing the impact of supply chain disruptions has been well-documented in numerous studies [221, 207]. Strategies such as backup suppliers, multi-sourcing, and the combination of several mitigation approaches have consistently been shown to enhance supply chain resilience, improving the ability to minimize disruption risks [222, 216, 223, 214, 224]. One approach explored the value of information sharing regarding the reliability of facilities. By integrating backup production capabilities, the study demonstrated how sharing real-time information about facility reliability helped firms coordinate responses to disruption risks better [225]. Emergency backup and storage facilities are widely recognized as an effective strategy to mitigate the impact of natural and anthropogenic hazards, such as floods, fires, power outages, and acts of malice [223]. Additionally, the importance of supplier flexibility in mitigating supply disruptions has been highlighted, as it allows firms to adapt more quickly to supply-side disruptions and respond with alternative sourcing strategies [226]. Building on these strategies, our model introduces random disruptions with varying levels of severity, evaluated over a multi-period time horizon. It examines multiple sourcing and backup facilities selected using a two-stage optimization model. Each supplier can be assigned as a primary or backup facility, optimizing disruption management across the supply chain over time.

Multi-period models are essential in capturing the dynamic of supply chain disruption, offering a detailed view of how mitigation strategies evolve across different phases. One study designed a multi-period mixed-integer model to analyze supply chain disruptions. In this model, a single disruption could occur within a defined time horizon and last for up to four periods. The researchers evaluated the model's response to disruption risks, providing insights into how supply chains can adapt and mitigate the impacts over multiple time periods [227]. Another study developed a two-stage stochastic programming model to manage long-term disruptions by considering profits, customer service levels, and market priorities. In this model, disruptions were allowed at multiple echelons, and decision-makers had to choose between contracting with primary or backup facilities, with interrupted facilities becoming unavailable during disruptions [228]. The expanded model also evaluated the performance of multiple mitigation strategies in response to different types of disruptions, from weak to strong, over a long time horizon, offering further insights into long-term resilience [229]. When a reduction in the capacity of an affected facility occurred, temporary or backup facilities were used to maintain operations. Our study differs from these by considering long-term decisions in the presence of multiple disruptions that can occur at both primary and backup facilities. We generate random disruptions characterized by varying lengths, random start times, and random post-disruption capacities. To reflect practical scenarios, our model assumes disrupted facilities enter a recovery phase where they can operate using available capacity, with a constant marginal increase in capacity throughout the recovery period. This approach allows for a more detailed analysis of recovery dynamics and facility management over the disruption period.

The two closest related papers to our study are that of [230] and [231] who proposed novel two-period model and two-stage stochastic programming model for multi-echelon supply chains under multiple disruptions, respectively. In the first paper, two planning horizons - before disruption and after disruption - are considered and one disruption occurs by the end of the planning horizon. The authors evaluated the financial performance of the model with recovery strategies to mitigate supply chain risks. The second paper focuses on profit maximization and discusses managerial implication to identify the impacts of disruptions at multiple echelons. The authors suggests recovery suppliers and decentralized strategy to minimize the disruptive impact and also noted that there is still a need to model risk when the severity and duration of disruption events are random parameters.

Table (4.1) summarizes the different features considered within the current supply chain network disruption literature. This table illustrates how our model differs from prior literature. Namely, our model considers all of the features together in one model, including allowing simultaneous disruptions at multiple echelons, accounting for varying levels of disruption severity, presenting a two-stage model that considers uncertainty, and allowing multi-sourcing and backup facilities at both the supplier and factory echelons.

Table 4.1: Literature review of mitigation strategies for supply chain networks under disruption

Authors	Disruption at multiple echelons	Disruption at multiple echelons simultaneously	Disruption with different severity levels	Two-stage with uncertainty	Multi-sourcing	Backup suppliers and/or factories	Recovery Time
[208]	x						
[209]	x		x				
[210]	x		x				
[207]	x				x		
[221]	x				x		
[223]						x	
[225]					x	x	
[232]					x		
[213]	x				x	x	
[218]	x				x	x	
[233]	x				x		
[214]					x		
[234]				x	x		
[235]	x		x				
[236]					x		
[216]			x	x	x	x	x
[212]			x		x		
[237]					x		
[219]			x	x	x	x	x
[222]	x		x	x	x	x	x
[230]	x		x		x	x	x
[238]	x				x	x	
[239]					x		
[220]			x	x	x		x
[217]	x	x		x	x		
[240]	x				x		
[241]	x		x	x	x	x	
[215]	x	x	x				x
[224]	x	x				x	x
[231]	x	x		x	x		
This paper	x	x	x	x	x	x	x

4.2.2 Food supply chain networks under uncertainties

Risk management in agricultural supply chains needs particularly more attention due to challenges associated with seasonality, supply risks, long lead times and perishability. Crop-based agricultural supply chains are typically classified into perishable or long life categories [199]. The OR field has developed optimization models that consider both the particular considerations needed to ensure freshness within perishable food supply chains [239, 241, 240] and long life product supply chains [236, 237]. The model we present is particularly well-suited for long-life agricultural products, yet extensions could be considered that incorporate the shelf life and special considerations for perishable products.

OR has a significant effect on improving the decision making processes in agricultural supply chains under uncertainty [242]. Stochastic programming with disruption uncertainties is used to support decision making in agricultural supply chain networks [232, 233]. A study employs a stochastic optimization model to address both supply-side and demand-side risks in a real-life multi-product case study within the agri-food industry [233]. To build on existing research, another study focuses on the global rice and wheat supply chains, proposing two post-disruption strategies, including using strategic national inventories and food substitution between rice and wheat to maintain supply stability [243]. A heuristic approach is applied to optimize these strategies, enabling efficient decision-making under disruption scenarios. Another study on the wheat supply chain developed a simulation model to assess the impact of transportation disruptions over a one-year period. The model evaluated various mitigation strategies and compared their effectiveness in terms of service level and total costs [244]. Another study provides insights into the effects of supply and demand fluctuations on the wheat supply chain by designing a scenario-based model that evaluates six scenarios over a one-year period [245]. To address the complexities of wheat supply chain optimization under uncertainty, a mixed robust and stochastic model was proposed to incorporate uncertainties in demand and supply across three scenarios, including optimistic, most likely, and pessimistic. This approach illustrated the significant impact of uncertainties on costs, facility locations, and network structure [246]. Additionally, responsiveness and resiliency in the wheat supply chain have been examined by incorporating delivery time, node complexity, and service level. The model is designed to minimize environmental and social impacts while addressing these critical aspects [247].

Building on insights from the literature, this study focuses on evaluating mitigation strategies for a three-echelon wheat supply chain facing multiple disruptions. The primary goal is to evaluate and strengthen supply chain resilience by designing a multi-period, two-stage stochastic model that incorporates disruptions of varying severity — categorized as low, medium, and high impact. To ensure a comprehensive representation of real-world disruptions, we generate numerous random scenarios, capturing a variety of disruption events across different time periods. Disruptions are modeled based on three key factors, including random duration, available capacity post-disruption, and timing of disruption events. These disruptions can impact both primary and backup facilities, with the possibility of multiple simultaneous occurrences. By integrating recovery strategies, such as multiple sourcing and backup facilities, this study provides practical insights for decision-makers aiming to enhance the resilience of agricultural supply chains.

4.3 Method

4.3.1 Agriculture supply chain under multiple disruptions

We propose a multi-echelon, two-stage stochastic program that accounts for the possibility of multiple disruptions occurring across different echelons of the supply chain. In this structure, items are sent from suppliers to factories and transported from factories to the warehouse, following a sequential flow across each echelon, see Figure 4.1. Disruptions are assumed to occur independently at nodes within various echelons, specifically suppliers and factories. Disrupted facilities are allowed to be concurrently unavailable, either fully or partially. Partial unavailability refers to instances where only a fraction of a facility's capacity is disrupted, allowing it to continue operating at a reduced level. Multiple mitigation strategies are incorporated to minimize disruption impacts and reduce the total amount of lost sales. Our optimization model supports resilience-focused decisions, evaluating whether the agribusiness should contract with backup suppliers and factories to address disruptions effectively. We assume constant demand over time, with all unsatisfied demand treated as lost rather than back-ordered when facilities cannot meet demand due to disruptions. Recovery costs for disrupted facilities are included based on the time required for full or partial recovery.

In the first stage of the model, primary and backup suppliers and factories are selected before any disruption, ensuring that the chosen primary facilities have sufficient capacity to meet demand. In the second stage, various disruptions are introduced across multiple scenarios. Each scenario has a specific probability and unique characteristics, such as the duration of the disruption, capacity reduction, and timing, which represent different levels of impact. To optimize the response, we assume that selected backup facilities are activated and allowed to produce only when at least one of the primary facilities is disrupted. The model aims to maximize supply chain productivity despite these disruptions. The decisions made in the second stage focuses on two key areas: (1) determining the quantity of products to be shipped between facilities in the supply chain network after disruption(s) and (2) calculating the amount of lost sales across primary and backup suppliers

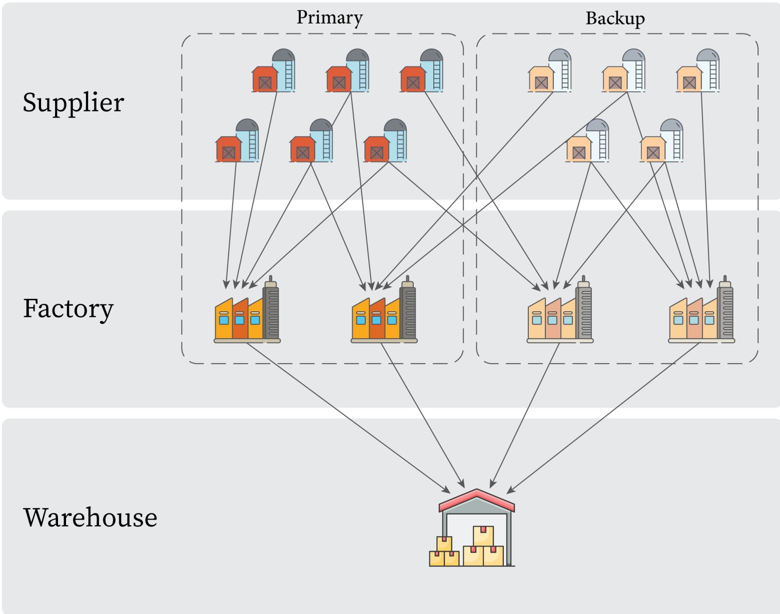


Figure 4.1: A multi-echelon agriculture supply chain network.

and factories for each scenario.

To address uncertainties, the proposed mitigation strategies include (a) using multiple sourcing rather than relying on a single source and (b) contracting with backup suppliers and factories to mitigate supply chain disruptions when primary facilities are affected. Additionally, a recovery process is integrated for disrupted facilities, incorporating a gradual increase in facility capacity during the recovery period to restore operational levels.

4.3.2 Problem Formulation

The sets, parameters, and decision variables defined for the mathematical model are as follows:

Sets and indices

N set of suppliers, index by n

M set of factories, index by m

Ω set of disruption scenarios, indexed by ω

T length of planning horizon

Input parameters (non-scenario dependent)

f_n^{ps} fixed cost per unit time of selecting supplier n as a primary supplier

f_n^{bs} fixed cost per unit time of selecting supplier n as a backup supplier

f_m^{pf} fixed cost per unit time of selecting factory m as a primary factory

f_m^{bf} fixed cost per unit time of selecting factory m as a backup factory

p_n^{ps} cost per bushel supplied by primary supplier n

p_n^{bs} cost per bushel supplied by backup supplier n

p_m^{pf} cost per bushel produced in primary factory m

p_m^{bf} cost per bushel produced in backup factory m

c_{nm}^{sf} cost per bushel transported from supplier n to factory m

c_m^{fw} cost per bushel transported from factory m to the warehouse

b cost of lost sales per bushel over the entire time horizon

v_n maximum capacity of supplier n over the entire time horizon

v_{nt} maximum capacity of supplier n at time t ($v_{nt} = \dfrac{v_n}{T}$)

v_m maximum capacity of factory m over the entire time horizon

v_{mt} maximum capacity of factory m at time t ($v_{mt} = \dfrac{v_m}{T}$)

D total demand over the entire time horizon

D_t averaged demand per unit time ($D_t = \dfrac{D}{T}$)

Input parameters (scenario dependent)

q^{ω} probability scenario ω occurs

$\lambda_{nt}^{s\omega}$ 1, if disruption occurs at supplier n at time t under scenario ω; otherwise, 0

$\lambda_{mt}^{f\omega}$ 1, if disruption occurs at supplier m at time t under scenario ω; otherwise, 0

$t_{n}^{s\omega}$ the time that a disruption starts at supplier n under scenario ω

$t_{m}^{f\omega}$ the time that a disruption starts at factory m under scenario ω

$\rho_{n}^{s\omega}$ fraction of capacity available immediately at supplier n following a disruption under scenario ω

$\rho_{m}^{f\omega}$ fraction of capacity available immediately at factory m following a disruption under scenario ω

$\Delta_{n}^{s\omega}$ marginal percentage increase in available capacity per unit time of disrupted supplier n under scenario ω

$\Delta_{m}^{f\omega}$ marginal percentage increase in available capacity per unit time of disrupted factory m under scenario ω

$r_{n}^{s\omega}$ cost per unit time to recover supplier n under scenario ω; takes 0 if no disruption at n occurs

$r_{m}^{f\omega}$ cost per unit time to recover factory m under scenario ω; takes 0 if no disruption at m occurs

$\theta_{n}^{s\omega}$ number of time periods needed to recover supplier n under scenario ω; takes 0 if no disruption at n occurs

$\theta_{m}^{f\omega}$ number of time periods needed to fully recover factory m under scenario ω; takes 0 if no disruption at m occurs

Decision variables

First-stage variables

X_{n}^{ps} binary variable, equal to 1 if supplier n is selected as a primary supplier; 0 otherwise

X_{n}^{bs} binary variable, equal to 1 if supplier n is selected as a backup suppliers; 0 otherwise

X_{m}^{pf} binary variable, equal to 1 if primary factory m is selected; 0 otherwise

X_{m}^{bf} binary variable, equal to 1 if factory m is selected as a backup factory; 0 otherwise

Scenario-based variables

γ^{ω}_{nmt}	the amount of demand transported from supplier n to factory m at time period t under scenario ω
σ^{ω}_{mt}	the amount of demand transported from factory m to the warehouse at time period t under scenario ω
B^{ω}_{t}	the amount of demand that is lost sales at time period t under scenario ω
$\tau^{s\omega}_{t}$	1 if there is a disruption at at any of the primary suppliers; otherwise, 0
$\tau^{f\omega}_{t}$	1 if there is a disruption at any of the primary suppliers; otherwise, 0

The first stage of the formulated problem is as follows:

$$\textbf{Stage 1:} \quad \text{P1 = Min} \quad |\text{T}|\big(\sum_{n\in N}(f^{ps}_n X^{ps}_n + f^{bs}_n X^{bs}_n) + \sum_{m\in M}(f^{pf}_m X^{pf}_m + f^{bf}_m X^{bf}_m)\big) + \sum_{\omega} q^{\omega} * \big(\sum_{n\in N} r^{s\omega}_n * X^{ps}_n * \theta^{s\omega}_n + \sum_{m\in M} r^{f\omega}_m * X^{pf}_m * \theta^{f\omega}_m\big) + \sum_{\omega} Q(X^{ps}, X^{bs}, X^{pf}, X^{bf}, \omega) \tag{4.1}$$

Subject to:

$$\sum_{n\in N} v_n * X^{ps}_n \geq D \tag{4.2}$$

$$\sum_{m\in M} v_m * X^{pf}_m \geq D \tag{4.3}$$

$$X^{ps}_n + X^{bs}_n \leq 1 \quad n \in N \tag{4.4}$$

$$X^{pf}_m + X^{bf}_m \leq 1 \quad m \in M \tag{4.5}$$

$$X^{ps}_n, X^{bs}_n \in \{0,1\} \quad n \in N \tag{4.6}$$

$$X^{pf}_m, X^{bf}_m \in \{0,1\} \quad m \in M \tag{4.7}$$

The objective function of the first stage (4.1) minimizes fixed cost plus expected recovery costs of primary facilities and expected costs of second stage over the time horizon. It includes an annual operating cost of selected facilities plus the expected supply chain cost after disruption. In the second stage, a sub-problem P_2 is solved for each disruption scenario, capturing the associated costs and decisions. The expected cost across all scenarios in the second stage, denoted by

$Q(X_n^{ps}, X_n^{bs}, X_m^{pf}, X_m^{bf}, \omega)$, is calculated as the weighted sum $\sum_\omega q^\omega \times P_2$, where q^ω represents the probability of each scenario.

Constraints (4.2) and (4.3) ensure that the total capacity of selected primary suppliers and factories is sufficient to meet the demand under normal conditions over the planning horizon. Constraint (4.2) focuses on the capacity of suppliers, while Constraint (4.3) addresses the capacity of factories, ensuring both are adequate to fulfill the total demand. Supplier n (factory m) cannot be both a primary and backup supplier (factory), constraints (4.4) and (4.5). The binary variables X_n^{ps}, X_n^{bs}, X_m^{pf}, and X_m^{bf} indicate the selection of primary and backup suppliers and factories, where a value of 1 represents selection and 0 indicates otherwise. These variables model the decision-making process for choosing suppliers and factories in the planning problem, constraints(4.6) and (4.7).

$$\textbf{Stage 2:}\quad \text{P2 = Min}\quad \sum_{t=1}^{T}\Bigg([\sum_{n\in N}\sum_{m\in M}\gamma^{\omega}_{nmt}(p^{ps}_{n}X^{ps}_{n}+p^{bs}_{n}X^{bs}_{n}) + \sum_{m\in M}\sigma^{\omega}_{mt}(p^{pf}_{m}X^{pf}_{m}+p^{bf}_{m}X^{bf}_{m})] + [\sum_{n\in N}\sum_{m\in M}c^{sf}_{nm}\gamma^{\omega}_{nmt} + \sum_{m\in M}c^{fw}_{m}\sigma^{\omega}_{mt}] + bB^{\omega}_{t} + \sum_{t=t^{s\omega}_{n}}^{t^{s\omega}_{n}+\theta^{s\omega}_{n}}\sum_{n\in N}r^{s\omega}_{n}*X^{bs}_{n}*\tau^{s\omega}_{t} + \sum_{t=t^{f\omega}_{m}}^{t^{f\omega}_{m}+\theta^{f\omega}_{m}}\sum_{m\in M}r^{f\omega}_{m}*X^{bf}_{m}*\tau^{f\omega}_{t}\Bigg) \tag{4.8}$$

Subject to:

$$\tau^{s\omega}_{t}\geq X^{ps}_{n}*\lambda^{s\omega}_{nt}\quad n\in N, 0<t\leq T \tag{4.9}$$

$$\tau^{f\omega}_{t}\geq X^{pf}_{m}*\lambda^{f\omega}_{mt}\quad m\in M, 0<t\leq T \tag{4.10}$$

$$\tau^{s\omega}_{t}\leq 1\quad 0<t\leq T \tag{4.11}$$

$$\tau^{f\omega}_{t}\leq 1\quad 0<t\leq T \tag{4.12}$$

$$\sum_{m\in M}\gamma^{\omega}_{nmt}\leq v_{nt}*(\sum_{n'\in N}(X^{ps}_{n'}*\lambda^{s\omega}_{n't})+X^{ps}_{n})\quad n\in N, 0<t\leq T \tag{4.13}$$

$$\sum_{m\in M}\gamma^{\omega}_{nmt}\leq (X^{ps}_{n}+X^{bs}_{n})*v_{nt}\quad n\in N,\ t\notin(t^{s\omega}_{n}, t^{s\omega}_{n}+\theta^{s\omega}_{n}) \tag{4.14}$$

$$\sum_{m\in M}\gamma^{\omega}_{nmt}\leq (\rho^{s\omega}_{n}+\Delta^{s\omega}_{n}(t-t^{s\omega}_{n}))(X^{ps}_{n}+X^{bs}_{n})*v_{nt}\quad n\in N;\ t^{s\omega}_{n}\leq t<t^{s\omega}_{n}+\theta^{s\omega}_{n} \tag{4.15}$$

$$\sum_{n\in N}\sum_{m\in M}\gamma^{\omega}_{nmt}\leq D_{t}\quad 0<t\leq T \tag{4.16}$$

$$\sigma^{\omega}_{mt}\leq v_{mt}*(\sum_{m'\in M}(X^{pf}_{m'}*\lambda^{f\omega}_{m't})+X^{pf}_{m})\quad m\in M, 0<t\leq T \tag{4.17}$$

$$\sigma^{\omega}_{mt}\leq (X^{pf}_{m}+X^{bf}_{m})*v_{mt}\quad m\in M;\ t\notin(t^{f\omega}_{m}, t^{f\omega}_{m}+\theta^{f\omega}_{m}) \tag{4.18}$$

$$\sigma^{\omega}_{mt}\leq (\rho^{f\omega}_{m}+\Delta^{f\omega}_{m}(t-t^{f\omega}_{m}))(X^{pf}_{m}+X^{bf}_{m})*v_{mt}\qquad m\in M,\ t^{f\omega}_{m}\leq t<t^{f\omega}_{m}+\theta^{f\omega}_{m} \tag{4.19}$$

$$\sum_{n\in N}\gamma^{\omega}_{nmt}-\sigma^{\omega}_{mt}\geq 0\quad m\in M;\ 0<t\leq T \tag{4.20}$$

$$\sum_{m\in M}\sigma^{\omega}_{mt}+B^{\omega}_{t}=D\quad 0<t\leq T \tag{4.21}$$

$$\gamma^{\omega}_{nmt}\geq 0\quad n\in N,\ m\in M, 0<t\leq T \tag{4.22}$$

$$\sigma^{\omega}_{mt}\geq 0\quad m\in M, 0<t\leq T \tag{4.23}$$

$$B^{\omega}_{t}\geq 0\quad 0<t\leq T \tag{4.24}$$

$$\tau^{s\omega}_{t},\tau^{f\omega}_{t}\geq 0\quad 0<t\leq T \tag{4.25}$$

Each disruption scenario $\omega \in \Omega$ occurs with probability q^{ω}. The goal is to minimize the second-stage cost across the entire time horizon for each scenario. In the objective function, the first two terms represent the production costs at the suppliers and factories. The third and fourth terms correspond to the transportation costs from suppliers to factories and from factories to the warehouse, respectively. The fifth term accounts for the cost of lost sales, while the final term represents the recovery costs for backup facilities when they are permitted to produce during their disruption period (4.46).

Constraints (4.9) and (4.10) are designed to identify whether any primary supplier or factory is disrupted. Specifically, Constraint (4.9) ensures that the decision variable $\tau_t^{s\omega}$ equals 1 if at least one primary supplier $n \in N$ is disrupted during period t. This is determined by the product of X_n^{ps}, which indicates that the primary supplier is selected, and $\lambda_{nt}^{s\omega}$, which indicates a disruption at the supplier. Similarly, Constraint (4.10) applies the same logic for factories, where $\tau_t^{f\omega}$ is set to 1 if at least one primary factory $m \in M$ is disrupted. The variable τ is helpful for determining when the selected backup suppliers and factories are able to start production, based on the assumption that backup facilities are utilized only when at least one primary facility is disrupted. Moreover, τ incorporates in calculating the recovery cost for backup facilities in the objective function (4.46), where the recovery cost is incurred only when these backup facilities are allowed to produce.

Constraints (4.11) and (4.12) ensure that $\tau_t^{s\omega}$ and $\tau_t^{f\omega}$ do not exceed 1, even if multiple primary suppliers or factories are disrupted, and are bounded below by 0. This formulation keeps τ as a continuous variable, which is necessary to comply with the assumptions of Benders Decomposition, where continuous variables are required in the second stage.

This constraints (4.13) and (4.17) ensures that backup facilities are only activated when necessary. Specifically, if a facility is selected as a backup, represented by X_n^{bs} (or X_m^{bf} for factories), then the corresponding primary facility, represented by X_n^{ps} (or X_m^{pf}), must be zero, indicating that it is not simultaneously acting as a primary facility. The summation $\sum_{n' \in N}(X_{n'}^{ps} \cdot \lambda_{n't}^{s\omega})$ captures the status of all primary facilities in the system. It becomes greater than 0 when at least one primary facility is disrupted. When this condition is met, it allows the backup facilities to start production. If no primary facilities are disrupted (the summation equals 0), the backup facilities are not permitted to produce, ensuring they only operate when needed for recovery.

Constraints (4.14) and (4.18) represent the maximum production capacity for the facilities. They ensure that each facility can utilize its full capacity when no disruptions occur. These constraints specify that the production level at each facility cannot exceed its maximum capacity under normal operating conditions.

The next set of constraints addresses scenarios when disruptions occur at the facilities. If a facility is affected, it can only utilize a fraction of its capacity immediately after the disruption. Constraints (4.15) and (4.19) represent the maximum available capacity of facilities after a disruption, limiting their production capacity. The parameter $\Delta_n^{s\omega}$ denotes a constant marginal increase in the capacity of a disrupted supplier n throughout the recovery period. When a disruption occurs, facilities may have zero available capacity or a small fraction of their capacity removed.

The following constraints, referred to as (4.16), ensure that the production shipped from suppliers to factories during each period t does not exceed the demand for that period. This effectively limits the amount of production transported, helping to align supply with demand over time. Additionally, constraints (4.20) maintain a balance between the incoming supply to each factory and its outgoing distribution to the warehouse, ensuring a consistent flow of goods throughout the network. Constraint (4.21) ensures that the total demand at period t is satisfied through shipments from factories to the warehouse or through lost sales. Specifically, the sum of transported demand $\sum_{m\in M}\sigma_{mt}^{\omega}$ and any unmet demand B_t^{ω} equals the total demand D_t. The shortfall is recorded as lost sales if shipments do not fully meet the demand. Constraints (4.22)-(4.25) define continuous decision variables greater than or equal to 0.

4.3.3 Assumptions

This section lists the main assumptions made in this study and explains their role in shaping the model and analysis. This study models a single-product, multi-echelon supply chain for a long life product under supply-side uncertainties. We assume that demand remains constant throughout the one-year time horizon, which is divided into 52 weeks. The model considers transportation costs, production costs, facility selection costs, lost sales and recovery costs over this time horizon to evaluate supply chain performance under disruption scenarios.

Lost sales are included instead of back-orders to account for unmet demand. Disruptions can occur at both suppliers and factories, affecting multiple echelons. While at most one disruption can impact a facility over the entire time horizon, both primary and backup facilities can experience multiple disruptions at different times. A detailed recovery plan for both types of facilities is outlined in the Recovery Plan Section.

The model allows for multiple facilities to be unavailable at the same time, either partially or fully. Partial unavailability refers to cases where only a fraction of a facility is disrupted, enabling it to continue operations using its remaining capacity. This assumption reflects a more flexible representation of facility capacities following disruptions.

The model generates different disruptions with varying intensities, categorized as low-, medium-, and high-impact disruptions. Random factors are used to generate disruptions, including the length of disruptions, start time, reduction rate in capacities after disruptions occur, and the random selection of facilities to be disrupted. For example, low-impact disruptions are characterized by shorter durations and lower reductions in capacity compared to medium- and high-impact disruptions. Disruptions for all categories can begin at any point within the time horizon, potentially leading to multiple disruptions at different facilities simultaneously. Low-impact events may result in zero or at least one disruption, whereas medium- and high-impact events always result in at least one disruption. This assumption ensures a flexible representation of disruption scenarios across the agricultural supply chain.

4.3.4 Recovery Plan

This section describes the recovery plan designed for facilities facing capacity disruptions, either fully or partially, within the supply chain network. Figure (4.2) illustrates the recovery process for supplier "n" when a disruption occurs at time $t_n^{s\omega}$, leading to an initial drop in capacity. During the recovery period, a constant marginal increase in capacity is applied to help restore operational levels, allowing the supplier to regain full functionality by the end of the specified recovery time. This structured recovery plan is similarly implemented across all factory nodes within the supply chain.

This recovery framework aims to provide a practical and realistic approach to managing disruptions, offering decision-makers insights into capacity restoration and associated costs. While acknowledging the model's limitations, we incorporate key characteristics to better approximate real-world conditions, supporting enhanced resilience in supply chains across various disruption scenarios.

4.3.5 Benders Decomposition Algorithm

The model we introduce is a complex, scenario-based mixed-integer program designed to address the uncertainties of disruptions across a multi-echelon supply chain. Given the model's complexity and many scenarios, directly solving this mixed-integer problem would be computationally intensive and inefficient. To manage this complexity, we apply benders decomposition, which is well-suited for large-scale, scenario-based models with distinct first- and second-stage

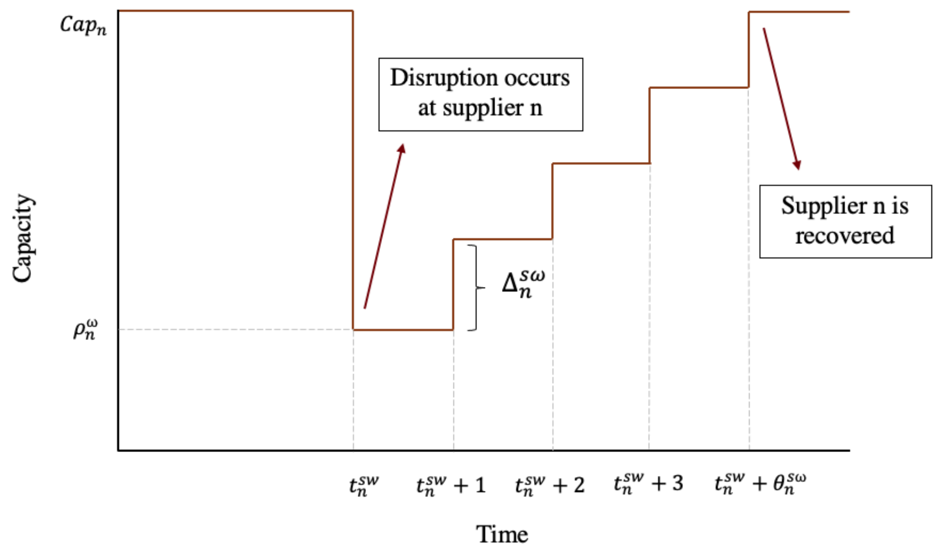


Figure 4.2: Capacity of supplier n during the recovery time

decisions [248]. Benders decomposition separates the original problem into two interconnected components: a master problem and subproblems. The master problem, as formulated in section 4.3.2 and denoted as P1, focuses on first-stage decisions, typically involving integer variables that represent strategic choices made prior to disruptions. In contrast, the subproblem addresses second-stage decisions involving continuous variables that align with specific disruption scenarios. These scenarios represent a range of disruption severities in the wheat supply chain. For each generated scenario, the subproblem adapts based on that disruption's unique conditions and intensity, enabling the model to evaluate the supply chain's resilience across varying potential disruptions. This separation aligns well with our model's structure and allows us for more efficient optimization. In the iterative Benders decomposition framework, the master problem (P1) determines the decisions on primary and backup facilities that the decision maker can contract with to satisfy demand. These decisions are represented by binary variables as X_n^{ps}, X_n^{bs}, X_m^{pf}, and X_m^{bf} , which are then supplied to the subproblem.

To generate cuts for the master problem (P1), a dual linear program of sub problem (P2) is introduced. The dual variables h_{nt}^{ω}, j_{mt}^{ω}, μ_t^{ω}, l_{nt}^{ω}, z_{nt}^{ω}, y_{nt}^{ω}, o_t^{ω}, η_{mt}^{ω}, e_{mt}^{ω}, g_{mt}^{ω}, k_{mt}^{ω}, and u_t^{ω} correspond to constraints (4.9) through (4.21). The Benders dual subproblem (DSP) can be expressed as:

$$\textbf{DSP:} \quad \text{P3 = Max} \quad \Bigg(\sum_{t=1}^{T} [\sum_{n\in N} (h_{nt}^{\omega'} * X_n^{ps} * \lambda_{nt}^{s\omega'}) + \sum_{m\in M} (j_{mt}^{\omega'} * X_m^{pf} * \lambda_{mt}^{f\omega'}) + \mu_t^{\omega'} + \psi_t^{\omega'}$$

$$+ \sum_{n\in N} l_{nt}^{\omega'} * v_{nt} * (X_n^{ps} + \sum_{n' inN} (X_{n'}^{ps} * \lambda_{n't}^{s\omega'})) \sum_{m\in M} \eta_{mt}^{\omega'} * v_{mt} * (X_m^{pf} + \sum_{m'\in M} (X_{m'}^{pf} * \lambda_{m't}^{f\omega'}))]$$

$$+ \sum_{n\in N} [\sum_{t=1}^{t_n^{s\omega'}-1} z_{nt}^{\omega'} * (X_n^{ps} + X_n^{bs}) * v_{nt} + \sum_{t=t_n^{s\omega'}+\theta_n^{s\omega'}}^{T} z_{nt}^{\omega'} * (X_n^{ps} + X_n^{bs}) * v_{nt}]$$

$$+ \sum_{t=t_n^{s\omega'}}^{t_n^{s\omega'}+\theta_n^{s\omega'}-1} \sum_{n\in N} (\rho_n^{s\omega'} + \Delta_n^{s\omega'}(t - t_n^{s\omega'}))(X_n^{ps} + X_n^{bs}) * v_{nt} * y_{nt}^{\omega'}$$

$$+ \sum_{m\in M} [\sum_{t=1}^{t_m^{f\omega'}-1} e_{mt}^{\omega'}(X_m^{pf} + X_m^{bf}) * v_{mt} + \sum_{t=t_m^{f\omega'}+\theta_m^{f\omega'}}^{T} e_{mt}^{\omega'}(X_m^{pf} + X_m^{bf}) * v_{mt}]$$

$$+ \sum_{t=t_m^{f\omega'}}^{t_m^{f\omega'}+\theta_m^{f\omega'}-1} \sum_{m\in M} (\rho_m^{f\omega'} + \Delta_m^{f\omega'}(t - t_m^{f\omega'}))(X_m^{pf} + X_m^{bf}) * v_{mt} * g_{mt}^{\omega'}$$

$$+ \sum_{t=1}^{T} (u_t^{\omega'} + o_t^{\omega'}) * D_t \Bigg) \tag{4.26}$$

Subject to:

$$\sum_{n\in N} h_{nt}^{\omega'} + \mu_t^{\omega'} \leq \sum_{n\in N} r_n^{s\omega'} \lambda_{nt}^{s\omega'} X_n^{bs} \qquad 0 < t \leq T \tag{4.27}$$

$$l_{nt}^{\omega'} + z_{nt}^{\omega'} + o_t^{\omega'} + k_{mt}^{\omega'} \leq p_n^{ps} X_n^{ps} + p_n^{bs} X_n^{bs} + c_{nm}^{sf}$$
$$\forall n \in N, m \in M; 0 < t < t_n^{s\omega'}; t_n^{s\omega'} + \theta_n^{s\omega'} \leq t \leq T \tag{4.28}$$

$$l_{nt}^{\omega'} + y_{nt}^{\omega'} + o_t^{\omega'} + k_{mt}^{\omega'} \leq p_n^{ps} X_n^{ps} + p_n^{bs} X_n^{bs} + c_{nm}^{sf}$$
$$\forall n \in N, m \in M; t_n^{s\omega'} \leq t < t_n^{s\omega'} + \theta_n^{s\omega'} \tag{4.29}$$

$$\sum_{m\in M} j_{mt}^{\omega'} + \psi_t^{\omega'} \leq \sum_{m\in M} r_m^{f\omega'} \lambda_{mt}^{f\omega'} X_m^{bf}$$
$$0 < t \leq T \tag{4.30}$$

$$\eta_{mt}^{\omega'} + e_{mt}^{\omega'} - k_{mt}^{\omega'} + u_t^{\omega'} \leq p_m^{pf} X_m^{pf} + p_m^{bf} X_m^{bf} + c_m^{fw}$$
$$\forall m \in M; 0 < t < t_m^{f\omega'}; t_m^{f\omega'} + \theta_m^{f\omega'} \leq t \leq T \tag{4.31}$$

$$\eta_{mt}^{\omega'} + g_{mt}^{\omega'} - k_{mt}^{\omega'} + u_t^{\omega'} \leq p_m^{pf} X_m^{pf} + p_m^{bf} X_m^{bf} + c_m^{fw}$$
$$\forall m \in M; t_m^{f\omega'} \leq t < t_m^{f\omega'} + \theta_m^{f\omega'} \tag{4.32}$$

$$u_t^{\omega'} \leq b \qquad 0 < t \leq T \tag{4.33}$$

$$h_{nt}^{\omega'} \geq 0 \qquad n \in N, 0 < t \leq T \tag{4.34}$$

$$l_{nt}^{\omega'} \leq 0 \qquad n \in N, 0 < t \leq T \tag{4.35}$$

$$\mu_t^{\omega'} \leq 0 \qquad 0 < t \leq T \tag{4.36}$$

$$z_{nt}^{\omega'} \leq 0 \qquad n \in N, 0 < t < t_n^{s\omega}; t_n^{s\omega} + \theta_n^{s\omega} \leq t \leq T \tag{4.37}$$

$$y_{nt}^{\omega'} \leq 0 \qquad n \in N, t_n^{s\omega} \leq t < t_n^{s\omega} + \theta_n^{s\omega} \tag{4.38}$$

$$j_{mt}^{\omega'} \geq 0 \qquad m \in M, 0 < t \leq T \tag{4.39}$$

$$\eta_{mt}^{\omega'} \leq 0 \qquad m \in M, 0 < t \leq T \tag{4.40}$$

$$e_{mt}^{\omega'} \leq 0 \qquad m \in M, 0 < t < t_m^{f\omega'}, t_m^{f\omega'} + \theta_m^{f\omega'} \leq t \leq T \tag{4.41}$$

$$g_{mt}^{\omega'} \leq 0 \qquad m \in M, t_m^{f\omega'} \leq t < t_m^{f\omega'} + \theta_m^{f\omega'} \tag{4.42}$$

$$k_{mt}^{\omega'} \geq 0 \qquad m \in M, 0 < t \leq T \tag{4.43}$$

$$o_t^{\omega'} \leq 0 \qquad 0 < t \leq T \tag{4.44}$$

$$u_t^{\omega'} \text{(free)} \tag{4.45}$$

In the Benders decomposition algorithm, the Benders cuts including Optimality cut 4.47 and Feasible cut 4.48 are generated by the Benders dual subproblem (P3) and incorporated into the master problem. We define the continuous variable Zas corresponding to the optimality cu, then the Benders master problem P1 are given by

$$\begin{aligned}
&\sum_{t=1}^{T}\Bigg([\sum_{n\in N}\sum_{m\in M}\gamma_{nmt}^{\omega}(p_n^{ps}X_n^{ps} + p_n^{bs}X_n^{bs})\\
&+\sum_{m\in M}\sigma_{mt}^{\omega}(p_m^{pf}X_m^{pf} + p_m^{bf}X_m^{bf})] + [\sum_{n\in N}\sum_{m\in M}c_{nm}^{sf}\gamma_{nmt}^{\omega} + \sum_{m\in M}c_m^{fw}\sigma_{mt}^{\omega}] + bB_t^{\omega}\\
&+\sum_{t=t_n^{s\omega}}^{t_n^{s\omega}+\theta_n^{s\omega}}\sum_{n\in N}r_n^{s\omega} * X_n^{bs} * \tau_t^{s\omega} + \sum_{t=t_m^{f\omega}}^{t_m^{f\omega}+\theta_m^{f\omega}}\sum_{m\in M}r_m^{f\omega} * X_m^{bf} * \tau_t^{f\omega}\Bigg) + \sum_{\omega\in\Omega}q^{\omega}Z^{\omega}
\end{aligned} \tag{4.46}$$

Subject to constraints (4.2) - (4.7).

$$\text{OBJ}_{DSP}^{\omega} \leq Z^{\omega} \qquad \omega \in \Omega \tag{4.47}$$

$$\text{OBJ}_{DSP}^{\omega} \leq 0 \qquad \omega \in \Omega \tag{4.48}$$

The benders decomposition algorithm is as follows:

Algorithm 1 Benders Decomposition Procedure

$UB \leftarrow \infty$, $LB \leftarrow 0$, $iter \leftarrow 0$
while $(UB - LB)/UB > \epsilon$ **do**
  Solve (P1)
  $LB \leftarrow E$ {the objective value of (P1)}
  Solve (P3)
  if (P3) is optimal **then**
    Add optimal cut (4.47) to (P1)
  else if (P3) is unbounded **then**
    Add feasibility cut (4.48) to (P4)
  end if
  Update UB if necessary
  $iter \leftarrow iter + 1$
end while

The Benders decomposition process solves the master problem and subproblem in turn. With each step, if the subproblem solution is feasible, an optimality cut is added to improve the master problem. If the subproblem is unbounded, a feasibility cut is added to address infeasibility. These cuts refine the solution with each iteration, progressively narrowing it to the best solution until the desired accuracy is achieved. This approach ensures that the model identifies an optimal and feasible solution across all scenarios.

4.4 Case Study

We designed a hypothetical wheat supply chain to evaluate mitigation strategies for managing disruptions in a multi-echelon network. The case study focuses on a single product, wheat, and includes key elements such as grain elevators and milling facilities, which are often vulnerable to disruptions. The hypothetical company aims to optimize decisions regarding supplier and factory selection while mitigating the impact of disruptions. This simplified model captures critical components of a real-world agricultural supply chain, allowing for a focused analysis of disruption impacts and the effectiveness of various mitigation strategies, see Figure 4.3.

Grain elevators serve as the first echelon in the supply chain, receiving wheat bushels from numerous farms and transporting them to milling facilities. Disruptions at this level can include

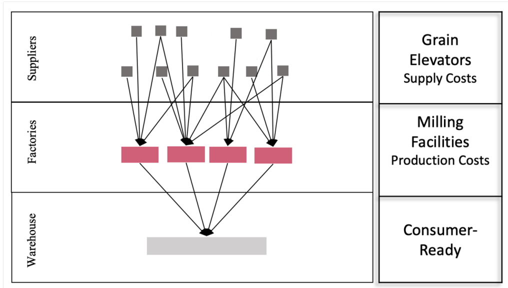


Figure 4.3: The structure of designed supply chain for a hypothetical wheat-product company

fluctuations in grain prices, transportation costs, infrastructure issues affecting roads and rail, and weather-related impacts on grain availability and timing [249]. Once received by milling facilities, the wheat is processed and transported to warehouses. At this second echelon, disruptions may result from unexpected downtime, production recalls, or shifts in demand, such as those triggered by COVID-19-related changes in restaurant and grocery needs. Our model captures a range of potential disruptions by categorizing them into low, medium, and high-impact events. Low-impact disruptions, such as minor equipment malfunctions or brief shipping delays, have minimal effects on overall supply chain performance. Medium-impact disruptions may involve labor shortages, significant equipment failures, or partial facility outages. High-impact disruptions, including natural disasters, pandemics, climate change effects, water shortages, pest outbreaks, farm-financial and political instability, can limit operational capacity and disrupt product availability [196, 250, 249]. This structured approach enables a detailed evaluation of mitigation strategies under various disruption scenarios.

4.4.1 Data

Table 4.3 provides the data used for our analysis, covering costs associated with facility selection, supply, milling production, maximum supplier and factory capacities, recovery, and lost sales. We based certain data estimates on publicly available information from Archer Daniels Midland Company (ADM), one of the largest agricultural supply chains in the world, ADM operates approximately 330 processing facilities and 520 procurement centers [249]. This extensive infrastructure connects raw commodities to consumer markets through complex logistics and production networks [249]. We estimated capacity values based on public ADMdata sources, given data limitations. ADM's facilities generally handle multiple products, so we adjusted capacities to align with a single-product supply chain model focusing exclusively on wheat. For example, grain elevators (suppliers) were assigned random capacities ranging between 10,000 and 50,000 units, while milling facilities (factories) were assumed to hold approximately double this range, from 50,000 to 100,000 bushels. This approximation aligns with publicly available capacity data [251, 252]. We also assumed that the fixed cost, representing the expense of contracting with each facility, varies based on facility capacity. This approach reflects the practical consideration that more extensive facilities with greater capacities generally involve higher contracting costs due to their increased operational scope and resource requirements.

Table 4.2 also lists the locations and number of suppliers and factories in this case study, representing a subset of ADM's facilities [253]. Since ADM inspires our model, we included a select number of facilities sufficient to meet demand, balancing model needs with practical constraints in data availability. Facilities with higher numbers have larger capacities and higher contracting costs. For example, Suppliers 11 and 12 are larger and more expensive to contract compared to others. There is a similar pattern for factories.

Table 4.2: Facility Locations

Suppliers		**Factories**	
Number	**Location**	**Number**	**Location**
1	Illinois	1	Indiana
2	Illinois	2	Indiana
3	Indiana	3	Kansas
4	Indiana	4	Kansas
5	Indiana	5	Kansas
6	Kansas	6	Missouri
7	Kansas		
8	Kansas		
9	Missouri		
10	Missouri		
11	Missouri		
12	Tennessee		

Transportation costs between suppliers, factories, and the warehouse were estimated based on facility locations and calculated by measuring the mileage between facilities and applying shipping rates per bushel by rail [254, 255]. We assumed that milling companies encounter higher production costs than grain elevators' supply (holding) costs, given the additional steps required to process raw grain into a finished product. Additionally, we estimated that larger facilities achieve lower production costs per bushel due to economies of scale [256]. Since precise cost data was unavailable for our model, we defined minimum and maximum values for production costs, setting each facility's production cost based on its capacity within this range. Facilities with higher numbers have lower production costs; for example, Supplier 11 and Factory 6 have the lowest production costs among suppliers and factories, respectively. The planning horizon in our model covers one year, precisely 52 weeks, which aligns with standard timeframes in agricultural supply chain studies [244, 245]. We use weekly units in the time component to represent short-term disruptions lasting less than a month accurately. This approach ensures that short-term and longer disruptions are effectively incorporated into the yearly decision-making process. Our two-stage model for the wheat supply chain under disruptions assumes an annual wheat demand of 100,000 bushels. While data on total wheat production is available through sources like the USDA, granular demand data specific to companies, such as ADM, is limited [257]. Certain variables, including the start time of each disruption, recovery duration, and post-disruption facility capacities across different scenarios, are estimated as random variables. The constant marginal increase in capacity during recovery is calculated by dividing the difference between maximum and post-disruption capacity by the disruption length. This calculation provides a steady increase, allowing capacities to return to full operation gradually over the recovery period. Each scenario in our model is assigned an equal probability.

4.4.2 Scenario Creation

We generated scenarios for each run to model varying disruption conditions in the supply chain. For our analysis, we used 100 scenarios per run, where each scenario is categorized into one of three impact levels such as low-impact, medium-impact, and high-impact. These categories are determined based on several random parameters and model assumptions that influence the severity of disruptions.

Key random parameters include the duration of disruptions and the percentage reduction in facility capacity. While these parameters have different ranges across the three impact categories, other factors also play a role in shaping the severity of disruptions. For example, the the random timing of when disruptions begin and the possibility of multiple disruptions occurring simultaneously at different facilities can increase the overall severity of disruptions in scenarios. In low-impact scenarios, disruptions may not occur at all, while medium- and high-impact scenarios always include at least one disruption.

For our analysis in the Results Section we considered two specific cases: the 90% low-impact distribution and the 90% high-impact case. The 90% low-impact case includes 90 low-impact

Table 4.3: Input data values for supply chain model analysis

Parameter	Value	Unit
f_n^{ps}	U(10,50)	1000-dollor per year
f_n^{bs}	U(10,50)	1000-dollor per year
f_m^{pf}	U(50,100)	1000-dollor per year
f_m^{bf}	U(50,100)	1000-dollor per year
D	100	1000 bushels per year
b	50	1000-dollor per 1000 bushels
$r_n^{s\omega}$	10	1000-dollor per supplier
$r_m^{s\omega}$	20	1000-dollor per factory
v_n	U(10,50)	1000 bushels
v_m	U(50,100)	1000 bushels
P_n^{ps}	(1,4)	1000-dollor per 1000 bushels
P_n^{rs}	(1,4)	1000-dollor per 1000 bushels
P_m^{pf}	(4,8)	1000-dollor per 1000 bushels
P_m^{rf}	(4,8)	1000-dollor per 1000 bushels
$t_n^{s\omega}$	U(1,50)	week
$t_m^{f\omega}$	U(1,50)	week
$\theta_n^{s\omega}$	U(1,10)	week (Low-impact)
$\theta_n^{s\omega}$	U(15,25)	week (Medium-impact)
$\theta_n^{s\omega}$	U(30,40)	week (High-impact)
$\rho_n^{s\omega}$	U(0, 0.2)	High-impact
$\rho_n^{s\omega}$	U(0.4, 0.6)	Medium-impact
$\rho_n^{s\omega}$	U(0.7, 1)	Low-impact
$\rho_m^{f\omega}$	U(0, 0.2)	High-impact
$\rho_m^{f\omega}$	U(0.4, 0.6)	Medium-impact
$\rho_m^{f\omega}$	U(0.7, 1)	Low-impact

disruption scenarios, five medium-impact, and five high-impact disruption scenarios. The 90% high-impact case consists of 90 high-impact disruption scenarios, five medium-impact, and five low-impact disruption scenarios. This setup represents highly volatile conditions dominated by severe disruptions, with minimal representation of less severe scenarios.

4.4.3 Case Study Results

We initially tested the model with different numbers of scenarios, including 50, 100, 300, and 500 scenarios per run, as shown in Table 4.4. It summarizes the solution times and optimality statuses for these runs across both the 90% low-impact and 90% high-impact cases, based on a single run for each scenario count. We observe that the model consistently solved the problems to optimality within 11 hours for 50, 100, and 300 scenarios across both distributions. However, for 500 scenarios, the model was solved to optimality for the 90% high-impact case but exhibited a 71% optimality gap for the 90% low-impact distribution after the 11 hour time limit, highlighting the increased computational effort required for larger scenario counts in the low-impact case. Additionally, the model consistently solved scenarios faster for the 90% high-impact case compared to the 90% low-impact case across all runs, regardless of the number of scenarios. Based on these observations, we selected 100 scenarios per run for further analysis. This choice represents a practical trade-off between computational time and the ability to capture a representative range of scenarios.

Table 4.4: Solution times (s) and status (solved or % gap) for problems within 11 hours.

Number of Scenarios	90% Low-Impact		90% High-Impact	
	Solution Times (s)	Status	Solution Times (s)	Status
50	9,513.1	solved	5,411.2	solved
100	15,110.5	solved	6,459.6	solved
300	37,230	solved	22,513	solved
500	39,600	71% (Gap)	30,084.7	solved

Note: Solution times are reported for a single run of the model.

Therefore, we proceed to analyze two cases to evaluate the impact of varying disruption patterns on supply chain performance, including 90% low-impact and 90% high-impact cases. Each case comprises 100 scenarios, and we conducted 10 independent runs for each. (That is, the 100 scenarios considered in run 1 are different than the 100 scenarios considered in run 2, for example). We evaluated key performance metrics for each distribution, including the objective function costs, the number of selected primary and backup suppliers and factories, their capacity utilization, and the total amount of lost sales. This comprehensive analysis provides insights into how varying disruption severity and frequency influences the effectiveness of mitigation strategies and overall supply chain resilience.

4.4.4 90% Low-impact Case

In this scenario distribution, 90 of the 100 scenarios represent low-severity disruptions, while medium- and high-severity disruptions are represented by five scenarios each. The average cost of the model's objective function, calculated over 10 runs, is $1,142,492.92, with a standard deviation of $46,554.8. This standard deviation is approximately 4% of the average objective function costs, indicating that the variation across runs is relatively low. The average computation time over these 10 runs is approximately four hours and 32 minutes.

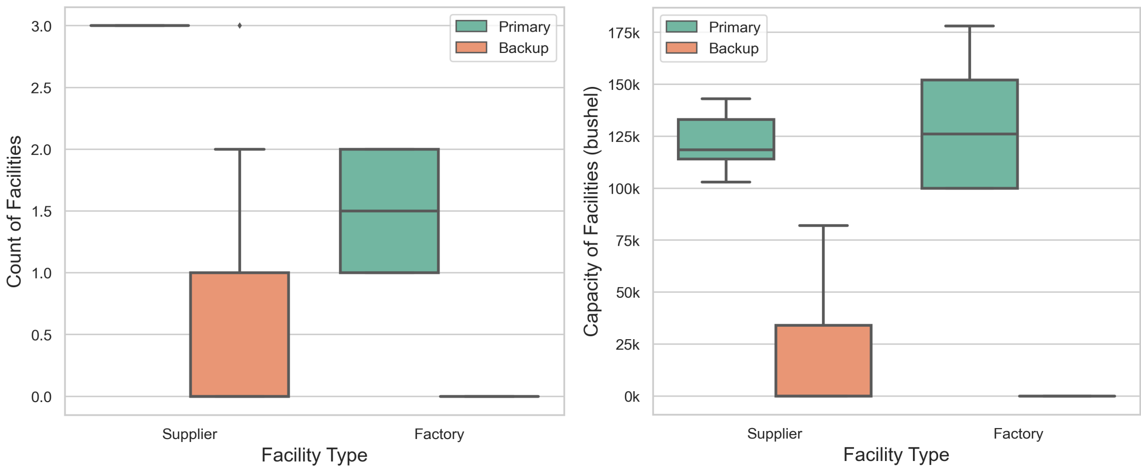
The optimal solution to all 10 runs selects three primary suppliers, see Figure 4.4a. However, the specific suppliers chosen differ between runs. Suppliers 11 and 12 frequently appear in the solutions, showing that the model often prefer larger suppliers. (As a reminder from the data section, facilities with a lower index are assumed to have lower capacities while facilities with higher indexes are assumed to have higher capacities. Larger facilities are characterized by lower production costs per bushel, despite having higher contract costs.) The number of primary factories selected fluctuates between one and two across the 10 runs. When the model selects only one primary factory, it consistently chooses the largest factory, Factory 6, which reflects its lower production costs despite higher fixed costs. In the runs where two factories are selected, Factory 5 is consistently chosen in combination with Factory 1, 3, or 4. This variability across runs may result from the interaction of different random factors in generating scenario disruption profiles and the model's optimization process, which seeks to minimize costs under varying conditions. The mean capacity of primary suppliers is 122,400 bushels, with a standard deviation of 13,201 bushels, while the mean capacity of primary factories is 130,300 bushels, with a standard deviation of 32,958 bushels. The higher mean capacity for factories reflects the input data, where factory capacities are higher than those of suppliers.

In terms of backup facilities: Six of the 10 runs show no selection of backup suppliers, while the others include one to three backup suppliers. The run with the highest selected backup capacity is 82,000 bushels, accounting for 20% of the total available capacity, see Figure 4.4b. The model did not select any backup factories in any of the 10 runs. Detailed facility selections for the model across these runs are presented in Table 4.5. Noting that the optimal solutions to the 10 runs exhibits variability with regard to the optimal facilities selected, we explore this variability further later in the results section to provide additional insights into its possible causes.

Table 4.5: Facility selection across 10 runs in 90% low-impact case

Run ID	Primary Suppliers	Backup Suppliers	Primary Factories	Backup Factories	Mean Unsatisfied Demand Across 100 Scenarios (1000-bushel)
1	7,10,11	6	4,5	-	0.017
2	9,10,12	-	6	-	1.52
3	1,11,12	-	6	-	1.22
4	7,10, 11	-	6	-	1.45
5	2,6,12	4	3,5	-	0.42
6	4,9,12	1,2,6	6	-	0.97
7	3,11,12	-	6	-	1.51
8	4,11,12	8,9	1,5	-	0.09
9	3,10,12	-	1,5	-	0.52
10	10,11,12	-	1,5	-	0.36

We analyzed the unsatisfied demand across all 100 scenarios per run. In nine out of 10



(a) Count of primary and backup facilities selected over 10 runs.

(b) Capacity selected by primary and backup facilities across 10 runs.

Figure 4.4: Facility selection and capacity analysis across 10 runs of 90% low-impact case

runs, the median unsatisfied demand is zero. This means that most scenarios in these runs do not experience lost sales. The highest average unsatisfied demand, calculated over 100 scenarios within a single run, is 1,526 bushels, which is about 1.5% of the total demand. These results show that the model effectively handles disruptions in this case. To better understand how different disruption severities affect the model's ability to meet demand, we analyzed unsatisfied demand across low-, medium-, and high-impact scenarios within the 90% low-impact case. The purpose of this analysis is to determine which severity levels contribute most to unsatisfied demand.

Therefore, we examined the median fraction of unsatisfied demand by disruption severity to uncover detailed patterns across low, medium, and high-impact scenarios, see Figure 4.5. For each run, the median fraction of unsatisfied demand is calculated separately for each severity level. For example, for high-impact scenarios, we compute the median fraction of unsatisfied demand over the five high-impact scenarios within that run. Similarly, for medium-impact scenarios, the median is calculated over the five medium-impact scenarios per run. For low-impact scenarios, which make up 90 scenarios per run, the median is derived from these 90 scenarios. The low-impact scenario shows that nine out of 10 runs have a median unsatisfied demand of zero, calculated across the 90 low-impact case in each run. For medium-severity scenarios, five out of 10 runs have a median unsatisfied demand of zero, meaning that in these runs, the median fraction of unsatisfied demand across the five medium-impact disruption scenarios is zero. In the remaining five runs, the median fraction of unsatisfied demand ranges from approximately 0.4% to 9%. These percentages represent a small proportion of the total demand of 100,000 bushels. High-impact scenarios exhibit greater variability, with the median unsatisfied demand across runs ranging from 0 to 14,850 bushels. This corresponds to approximately 0% to 14.8% of the total demand of 100,000 bushels. These percentages represent the median proportion of unsatisfied demand calculated over the five high-impact disruption scenarios in each run. They do not represent the model's overall performance for the 90% low-impact case, as they do not account for the total lost sales across all 100 scenarios. This analysis indicates that high-impact disruption scenarios contribute most significantly to unsatisfied demand within the case.

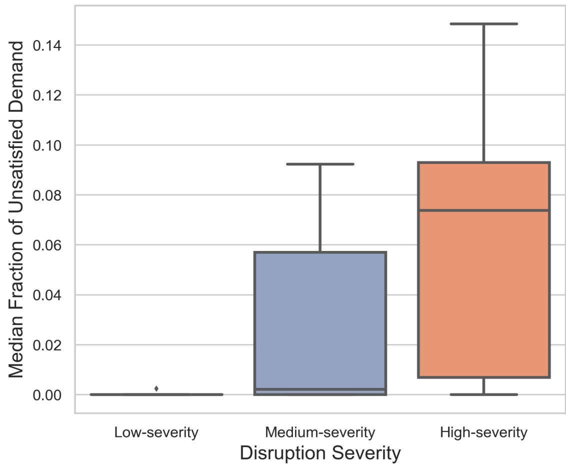
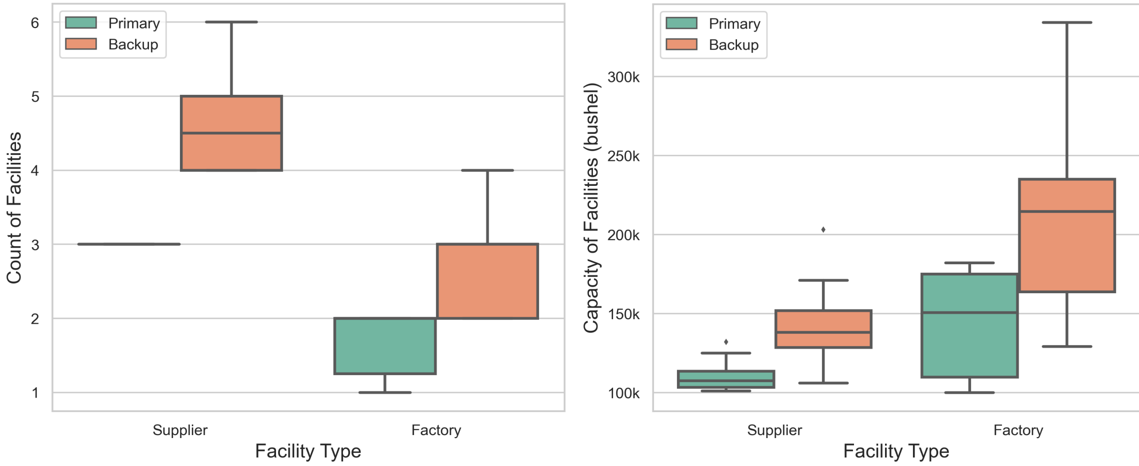


Figure 4.5: Median fraction of unsatisfied demand across low, medium, and high-impact scenarios under 90% low-impact case, showing higher variability and number of lost sales in high-impact scenarios.

4.4.5 90% High-impact Case

In this case, 90 out of the 100 scenarios are high-impact disruptions, while the remaining 10 scenarios are evenly split, with five low-impact and five medium-impact disruptions. The average cost of the model's objective function, calculated over ten runs, is \$2,604,781, with a standard deviation of \$273,349.8. The standard deviation is approximately 10% of the average objective function costs which is higher than that observed in the 90% low-impact case, indicating greater variability in costs under this distribution. The average computation time over these 10 runs is approximately one hour and 37 minutes.

Again, the optimal solution to all 10 runs selects three primary suppliers, see Figure 4.6a. However, the specific primary suppliers selected vary between runs. The number of backup suppliers ranges from four to five facilities. For primary factories, the number fluctuates between one and two, while the number of selected backup factories varies between two, three, and four.



(a) Count of primary and backup facilities selected over ten runs.

(b) Capacity selected by primary and backup facilities across ten runs.

Figure 4.6: Facility selection and capacity analysis across ten runs of 90% high-impact distribution

The average capacity of primary suppliers selected over 10 runs is 110,800 bushels, with a standard deviation of 10,486 bushels. The average capacity for backup suppliers is 143,400 bushels, with a standard deviation of 27,842 bushels, see Figure 4.6b. The mean capacity of primary factories, calculated over 10 runs, is 144,400 bushels, with a standard deviation of 34,027 bushels. In comparison, the mean total capacity of backup factories is 214,400 bushels, with a standard deviation of 64,278 bushels. This indicates that the total capacity variability among factories is higher than that of suppliers. In the 90% high-impact case, the total capacity allocated to backup facilities is higher than that allocated to primary facilities. This illustrates a preference for utilizing backup facilities to address severe disruptions.

We analyzed the unsatisfied demand across all 100 scenarios per run for the 90% high-impact case. In all 10 runs, the median unsatisfied demand is zero, indicating that the majority of scenarios in each run do not experience lost sales. The highest average unsatisfied demand, calculated over 100 scenarios within a single run, is 194 bushels, which accounts for about 0.19% of the total demand. These results demonstrate that the model effectively manages disruptions in this distribution, with minimal lost sales even under high-impact conditions. Additionally, we explore how lost sales vary across different severity levels of scenarios to gain further insights.

Next, we explored the fraction of unsatisfied demand across disruption severity levels. In the 90% low-impact case results, we presented results for the *median* fraction of unsatisfied demand across the low, medium, and high-imapct scenarios. However, unlike the 90% low-impact case, the median unsatisfied demand is zero for all severity levels in the 90% high-impact case. Therefore, we visualize the *mean* fraction of unsatisfied demand across disruption severity levels. The Figure 4.7 shows that the most extreme case is one run where the maximum mean unsatisfied demand over high-impact scenarios is 216 bushels out of 100,000 bushels of demand. This represents a very small fraction of the total demand. Additionally for low- and medium-impact scenarios, both the total and median unsatisfied demand are zero in every run, meaning all demand was fully satisfied for these scenarios. For high-impact scenarios, the median unsatisfied demand is zero in each of the ten runs. This shows that most of the 90 high-impact scenarios per run have no unsatisfied demand. However, the total unsatisfied demand for high-impact scenarios is greater than zero, indicating that a small number of these scenarios experience unsatisfied demand, contributing to lost sales.

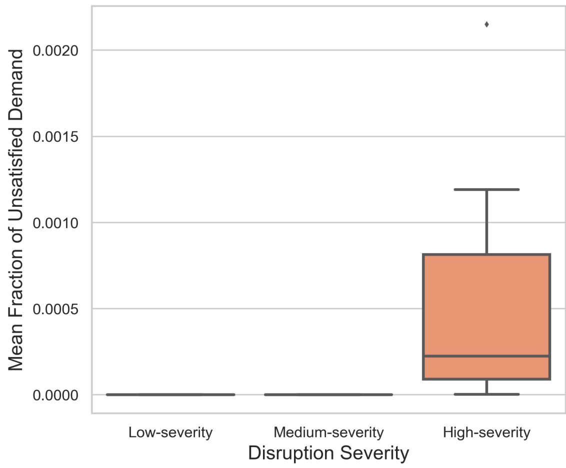


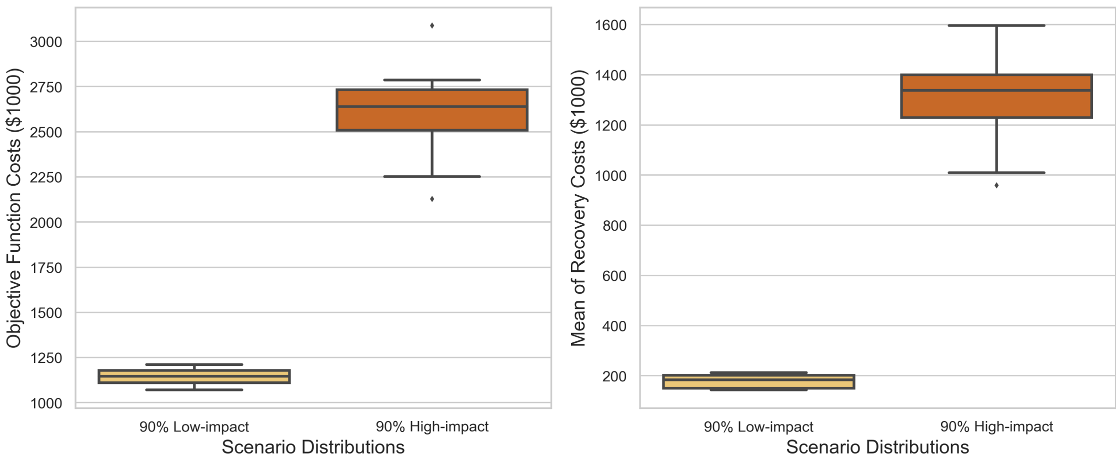
Figure 4.7: Mean of unsatisfied demand across low, medium, and high-impact scenarios under 90% high-impact case, showing higher variability in high-impact disruption scenarios.

4.4.6 Comparison of Two Cases

To gain deeper insights into the model's performance, we compare key characteristics across the two cases, including 90% low-impact and 90% high-impact cases. This comparison focuses on total objective function costs, facility costs, recovery costs and unsatisfied demand.

The analysis reveals that the objective function consistently increases with the severity of disruptions in the cases 4.8a. This trend is expected as higher-impact disruptions demand more resources and mitigation strategies, resulting in higher overall costs. Figure 4.9a illustrates that the model allocates higher overall facility costs in the 90% high-impact case compared to the 90% low-impact case. Figure 4.9a provides a detailed breakdown of mean facility costs over 10 runs for each scenario case. The figures reveal that in the 90% low-impact case, the model allocates a higher proportion of facility costs to primary facilities, whereas in the 90% high-impact case, it spends a higher percentage of facility costs on backup facilities.

In addition, an interesting pattern emerges when we analyze recovery costs, as these costs rise from scenarios with 90% low-impact to 90% high-impact cases. This indicates that cases with a higher percentage of low-impact scenarios experience lower recovery costs, as shown in Figure 4.8b. When comparing the model's behavior in the 90% low-impact and 90% high-impact cases, we notice differences in how costs are allocated. In the 90% low-impact case, the model appears to focus on minimizing total costs by avoiding reliance on backup facilities, which helps keep recovery costs lower. On the other hand, in the 90% high-impact case, the model allocates more resources to handling intense disruptions, resulting in higher recovery, facility and total costs. These patterns suggest that the model adjusts its cost allocation strategies in response to the severity of disruptions.

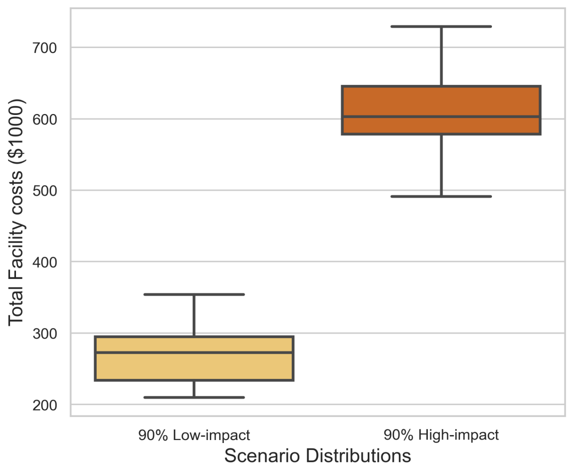


(a) Minimized total cost of the objective function: total cost values in $1000 under various scenario distributions.

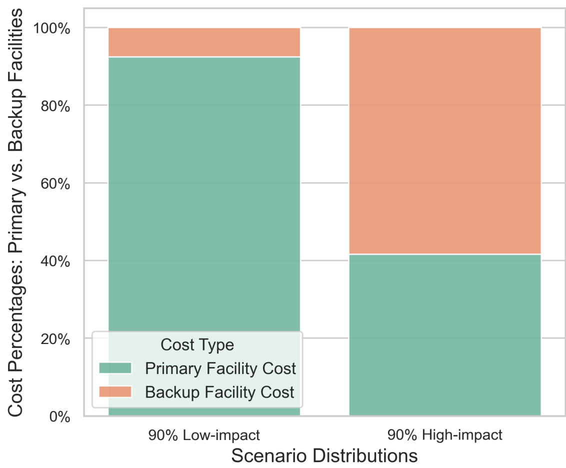
(b) Mean of recovery costs over 100 scenarios per run: It includes recovery costs for suppliers and factories, presented in $1000.

Figure 4.8: Objective function costs and recovery costs per scenario disruption.

Interestingly, we observed that the variability of the mean unsatisfied demand over 100



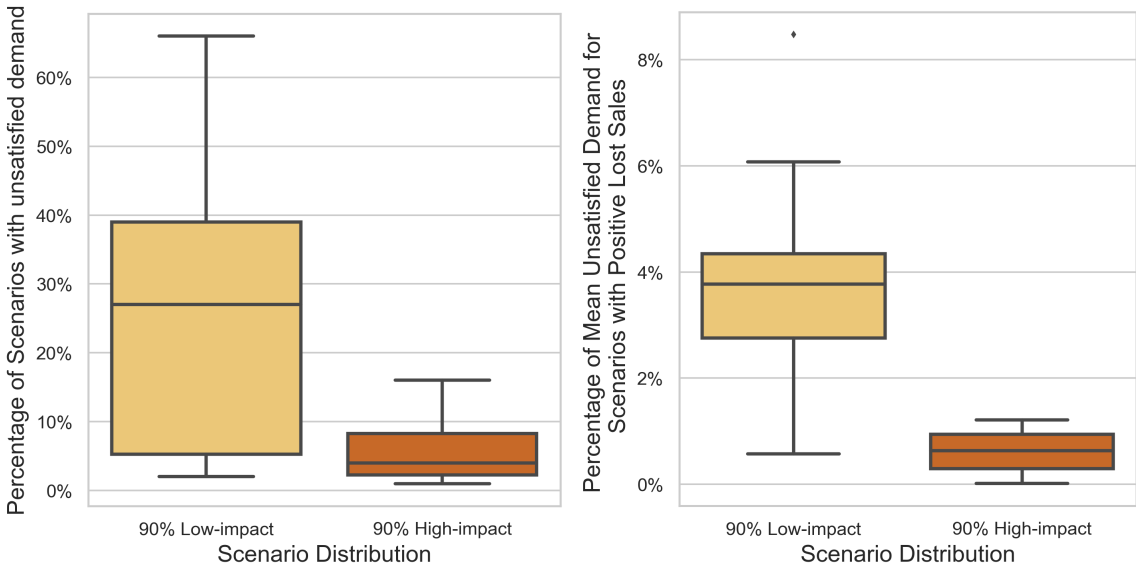
(a) Comparison of total facility costs across scenario distributions.



(b) Percentage of mean facility costs: it compares primary and backup facility cost percentages between two scenario distributions, based on the mean costs over ten runs.

Figure 4.9: Comparison of facility costs between 90% low-impact and 90% high-impact distributions.

scenarios is higher in the 90% low-impact case than the 90% high-impact case, as mentioned in the 90% low-impact and 90% high-impact cases. We build on an earlier observation that the median unsatisfied demand over 100 scenarios is consistently zero for nine out of 10 runs in 90% low-impact case, while in the 90% high-impact case, the median unsatisfied demand is zero for all ten runs. This finding suggests that many scenarios per run experience no lost sales, while a few contribute to the total unsatisfied demand. Since the mean is not an efficient measure in this case due to high variability, we investigate the percentage of scenarios with unsatisfied demand. Figure 4.10a shows that the maximum percentage of scenarios with unsatisfied demand is 66% of the 100 scenarios within a run for the 90% low-impact case, compared to less than 20% in the 90% high-impact case. Figure 4.10b further examines the mean percentage of unsatisfied demand for scenarios with positive unmet demand, showing that, despite higher variability in the 90% low-impact distribution, unmet demand remains relatively low at an average of 8.4%, compared to less than 2% in the 90% high-impact case. These analyses collectively provide a clearer understanding of the model's performance, indicating that it effectively meets demand in most scenarios.



(a) Percentage of scenarios with unsatisfied demand: shows the proportion of scenarios with lost sales.

(b) Percentage of mean unsatisfied demand: displays the mean unsatisfied demand, expressed as a percentage of the total demand, calculated only for scenarios with lost sales.

Figure 4.10: Comparison of the proportion of scenarios with unsatisfied demand and the average unsatisfied demand relative to total demand across different scenario distributions.

4.4.7 Examining the Variability in Optimal Solutions

We choose the 90% low-impact distribution for further analysis, as it is more likely to reflect disruption patterns in wheat supply chains. Although detailed data on the frequency and severity of disruptions in these supply chains is limited, previous studies have indicated that low-impact disruptions tend to occur more frequently, while high-impact disruptions are less frequent but have more severe consequences [258, 259]. Given the lack of specific data, we assumed that low-impact disruptions, such as minor transportation delays or small-scale equipment failures, occur most frequently. In comparison, medium-impact disruptions, including labor shortages, partial facility outages, or serious equipment failures, and high-impact disruptions, such as droughts, floods, water shortages, or pest outbreaks, are less frequent but have the most significant impact when they occur.

In the 90% low-impact distribution, we observe variability in facility selection across the 10 runs, see Table 4.5. This variability poses challenges for agribusinesses in deciding which facilities, primary or backup, to contract with to reduce the impact of disruptions. We examine this variability to gain meaningful insights into the model's performance. To explore it further, we analyze how the objective function is affected when facility selections from each run are applied to Run 1. The purpose of this analysis is to evaluate whether the variability in facility selection leads to significant differences in cost. If applying facility selections from other runs results in a large increase in the objective function, it would suggest that variability poses a significant challenge. Conversely, if the differences are small, this would indicate that the facility selections across runs are near-optimal solutions, and the variability is less of a concern. Figure 4.11 illustrates the percentage differences in the objective function when facility selections from other runs are applied to Run 1. The analysis shows that when the facility selections from the other nine runs are applied to Run 1, six out of nine comparisons result in differences of less than 2%, accounting for approximately 66% of the cases. This suggests that in the majority of cases, the facility selections from other runs perform close to the optimal solution for Run 1. One comparison shows a difference of approximately 6%, while the remaining two exhibit differences between 6% and 10%.

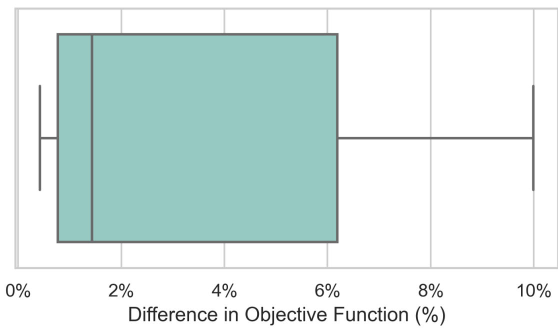
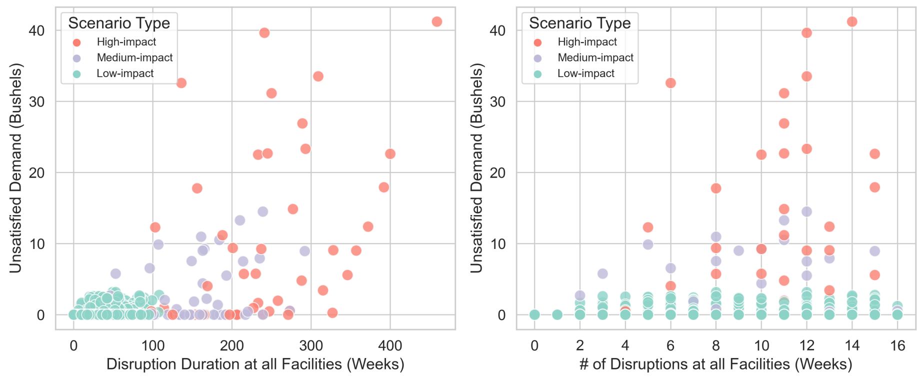


Figure 4.11: Percentage differences in the objective function when facility selections from other runs are applied to Run 1.

To better understand what parameters within the model may be causing this variability, we next examine the disruption profiles across the ten runs in the 90% low-impact distribution. While the distribution of disruption severities remains the same across runs, the scenarios are generated with multiple randomly assigned parameters, leading to multiple sources of uncertainty within the data. These parameters include the duration of disruptions, the timing of when disruptions begin, the reduction in capacity after disruptions, and the facilities affected by disruptions. Each parameter has different ranges within the uniform distributions for low-, medium-, and high-impact scenarios, contributing to variability in scenario severity and frequency. The assumptions in our scenario generation process can lead to a wide range of different disruption situations. For instance, multiple disruptions can occur simultaneously, there are no fixed limits on the number of disrupted facilities, and facilities can be partial or fully unavailable. Although these assumptions help create scenarios that reflect conditions closer to real-world disruptions, it also presents challenges in interpreting the model's behavior.



(a) The relationship between the total length of disruptions and the corresponding unsatisfied demand per scenario across 10 runs.

(b) The relationship between the total number of disruptions and the corresponding unsatisfied demand per scenario across 10 runs.

Figure 4.12: Comparison of disruption characteristics and unsatisfied demand per scenario across ten runs in the 90% low-impact distribution.

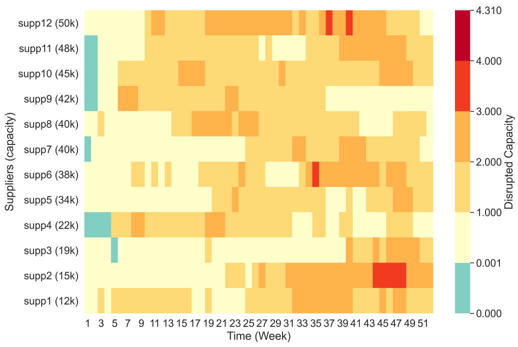
Therefore, we conduct an analysis to identify the characteristics of disruption scenarios that impact the model's ability to meet demand. We explored the relationship between unsatisfied demand and two key factors such as total length of disruptions and the total number of disruptions across all facilities. Figure 4.12a shows the relationship between unsatisfied demand (in bushels) and the total disruption duration (in weeks) across all facilities. Each point in the plot represents a single scenario from one of the ten runs, categorized by scenario type, including low-impact (green), medium-impact (purple), and high-impact (orange). Therefore, the plots contain 1,000 data points. Low-impact scenarios are clustered near the origin, with short disruption durations and minimal unsatisfied demand, indicating the model's ability to handle disruptions effectively in these cases. Medium-impact scenarios are more dispersed, showing moderate disruption durations and higher unsatisfied demand than low-impact scenarios. High-impact scenarios, however, show the widest range, with disruption durations exceeding 400 weeks and unsatisfied demand reaching up to 40 bushels.

Similarly, Figure 4.12b examines the relationship between unsatisfied demand (in bushels) and the *total number of disruptions* across all facilities. The plot shows signs of a correlation between the total number of disruptions and unsatisfied demand, particularly for high-impact scenarios. We statistically analyzed the correlation between unsatisfied demand and the two key factors such as the total number of disruptions and the total length of disruptions. The results confirm significant correlations between both factors and unsatisfied demand, with stronger relationships observed for high-impact scenarios, see Table 4.6.

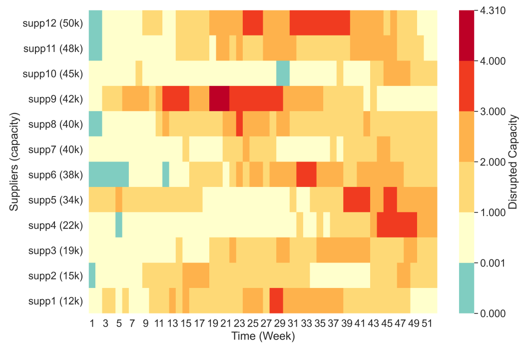
Table 4.6: Spearman correlations between disruption characteristics and lost sales

Disruption Type	**Length of Disruptions**	**# of Disruptions**
Low-impact	0.1127 (P-value: 7.05×10^{-4})	0.1250 (P-value: 1.69×10^{-4})
Medium-impact	0.3672 (P-value: 0.0087)	0.3023 (P-value: 0.0328)
High-impact	0.5403 (P-value: 5.12×10^{-5})	0.5734 (P-value: 1.35×10^{-5})

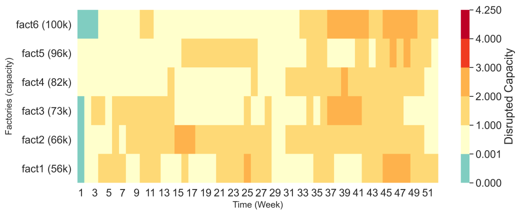
The following analysis explores the disrupted capacity over the time horizon for each run to investigate further the factors contributing to variability in facility selection. By examining the disrupted capacity across facilities over time, we aim to uncover patterns that may explain some of the observed variability in the model's facility selection decisions. To reduce the complexity of presenting all 10 runs, we selected a subset of representative plots to highlight the key findings. Specifically, Figure 4.13 visualizes the percentage of total capacity disrupted at each period for each supplier and factory in runs 2 and 8. Each cell represents the total disrupted capacity across 100 scenarios at a given time in each run, highlighting the cumulative impact of disruptions over time. To illustrate how the fraction of total disrupted capacity is calculated at each time period, consider the example of Supplier 1 at time period 1. Suppose Supplier 1 experiences no disruptions in 70 scenarios, while in the remaining 30 scenarios, it operates at 50% of its capacity due to disruptions. To calculate the fraction of disrupted capacity for this time period, we multiply the disruption level by the number of scenarios for each case. In this example, 70 scenarios have no disruptions, contributing zero to the disrupted capacity, while 30 scenarios with 50 percent disruption contribute to the total. Adding these, we find that 15 percent of Supplier 1's total capacity is disrupted at time period 1 across all 100 scenarios. The colors in the heat maps represent the percentage reduction in capacity at each period. Darker red indicates a higher percentage of capacity reduction at a specific time, while green shows that the facility's capacity is fully available. Overall, comparing the Figures 4.13a and 4.13b shows that the reduction in capacity is higher at different periods in run 8 compared to run 2. To mitigate these disruptions, the model selects backup suppliers, such as Suppliers 8 and 9, in run 8 to ensure demand is met effectively.



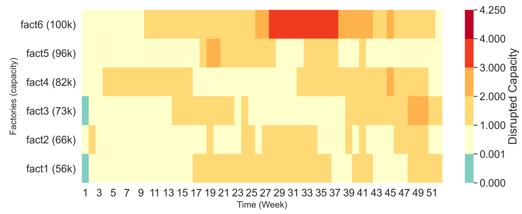
(a) Fraction of total disrupted capacity for suppliers over time horizon in run 2, calculated across 100 scenarios.



(b) Fraction of total disrupted capacity for suppliers over time horizon in run 8, calculated across 100 scenarios.



(c) Fraction of total disrupted capacity for factories over time horizon in run 2, calculated across 100 scenarios.

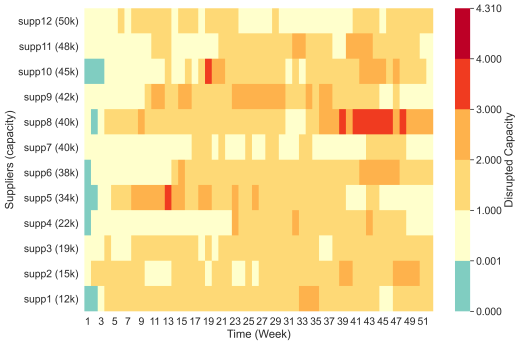


(d) Fraction of total disrupted capacity for factories over time horizon in run 8, calculated across 100 scenarios.

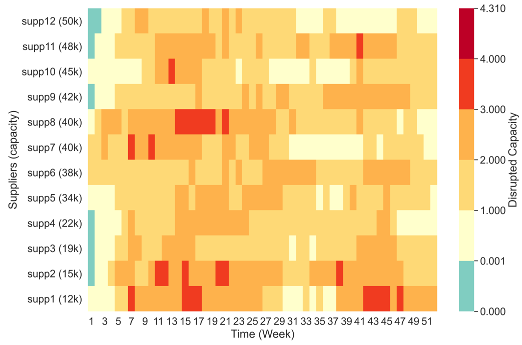
Figure 4.13: Patterns in total disrupted capacity over the time horizon for suppliers and factories across runs 2 and 8, calculated over 100 scenarios per run.

In run 2, Factory 6 shows a lower percentage of disrupted capacity, making it a good choice for the model because it is the largest factory with lower production costs, see Figure 4.13c. In contrast, in run 8, Factory 6 experiences significant capacity reductions over multiple time periods, as indicated by the darker red cells, see Figure 4.13d. This may lead the model to select Factories 1 and 5 instead. The following Figure 4.14 compares the disrupted capacity distributions over time for runs 1 and 4, highlighting key differences in how the model responds to varying disruption profiles. Run 4 shows a more even distribution of disruptions over the time horizon, with intense capacity reductions (darker red) spread across multiple periods. In contrast, run 1 has periods with minimal disruptions (lighter colors) and others with concentrated reductions. Although the model selects primary suppliers 7, 10, and 11 in both runs, it includes backup supplier 6 in run 1 but not in run 4.

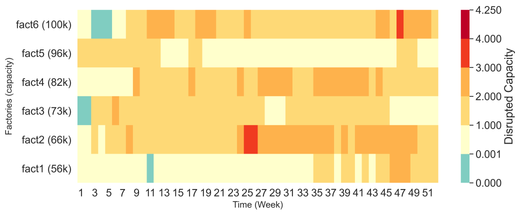
The heatmaps reveal that supplier 6 experiences a higher total duration of disruptions and greater reductions in capacity in run 4 compared to run 1. This may explain why the model did not select supplier 6 as a backup in run 4, as its higher levels of disruption could limit its effectiveness in mitigating disruptions. The differences likely explains the selection of factory 6 in run 4, where disruptions were less severe.



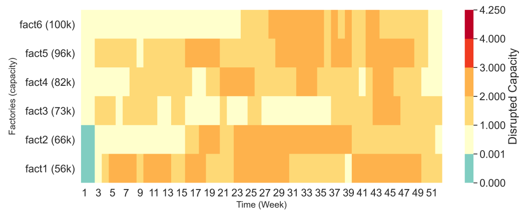
(a) Fraction of total disrupted capacity for suppliers over time horizon in run 1, calculated across 100 scenarios.



(b) Fraction of total disrupted capacity for suppliers over time horizon in run 4, calculated across 100 scenarios.



(c) Fraction of total disrupted capacity for factories over time horizon in run 1, calculated across 100 scenarios.



(d) Fraction of total disrupted capacity for factories over time horizon in run 4, calculated across 100 scenarios.

Figure 4.14: Patterns in total disrupted capacity over the time horizon for suppliers and factories across runs 1 and 4, calculated over 100 scenarios per run.

4.5 Discussion and Conclusion

We developed a two-stage stochastic model to evaluate mitigation strategies for a multi-echelon, single-product supply chain in the agricultural sector. The model incorporates various disruption profiles designed using random factors, enabling the generation of multiple sources of uncertainty with varying intensities.

To assess the model's performance, we studied its behavior under two cases: 90% low-impact and 90% high-impact disruption scenarios. In the 90% low-impact case, the model exhibited lower minimized objective function costs compared to the 90% high-impact case. This outcome is attributed to reduced efforts in selecting factories and recovery costs due to the less severe nature of disruptions. However, the 90% low-impact case also resulted in higher unsatisfied demand than the high-impact case, as the model allocated fewer resources to mitigating disruptions.

The model's flexibility lies in its ability to adjust to decision-makers' preferences through changes in the lost sales cost. Increasing the lost sales penalty encourages the model to allocate more resources toward satisfying demand, even if this results in a higher total objective function cost. This provides decision-makers with the ability to prioritize demand satisfaction over cost minimization when necessary, allowing for a balanced approach to managing trade-offs in the supply chain.

In the 90% low-impact case, which we focused on as it more closely reflects disruption patterns in the agricultural supply chain, we observed variability in facility selection across 10 runs. Although all runs had an equal distribution of disruptions, the variability appears to be influenced by the characteristics of the disruptions generated. This aligns with our assumption that disruptions are defined by random factors such as length, start time, reduction rate in capacities, and the random selection of facilities. For example, our analysis showed that the length and number of disruptions significantly correlate with the model's decisions on unsatisfied demand.

Additionally, the assumption that disruptions can vary in intensity—categorized as low-, medium-, and high-impact—helps explain why the intensity of disruptions differs across the 10 runs, leading to differences in facility selection. For instance, in some runs with shorter and less severe disruptions, the model prioritized minimizing costs by selecting fewer facilities, while in runs with longer and more severe disruptions, the model allocated more resources to mitigate the impact, resulting in a different set of facilities being selected.

This variability highlights the challenges that come from relying on assumptions about random factors and disruption intensities. The differences in facility selection across the 10 runs make it difficult for agribusinesses to identify a consistent strategy for mitigating disruptions and satisfying demand.

The model has some limitations that should be acknowledged. Firstly, it assumes that demand remains constant throughout the one-year time horizon. This does not account for potential fluctuations in demand that may occur in real-world agricultural supply chains, which could influence the results. Secondly, the model assumes that each facility can experience at most one disruption over the entire time horizon. This assumption was made to reduce the complexity of the modeling and computational process. Thirdly, using numerous random factors in generating disruption profiles introduced variability in the model's results. While these factors allow for diverse and realistic scenarios, they also created challenges in achieving robust and consistent results. This variability made it more difficult to conduct a comprehensive analysis and perform sensitivity analyses to deeply explore the model's behavior.

Several directions for future work could enhance the current study. One avenue is to consider both supply-side and demand-side uncertainties, which would provide a more comprehensive understanding of disruptions and their impact on supply chain performance.

Another direction involves refining the approach to generating disruption and scenario profiles. Since we observed that the combination of random factors (e.g., disruption length, start time, and capacity reduction) significantly impacts the results, future work could explore the model's behavior by varying one factor while keeping the others constant. Repeating this process for different factors would allow a deeper investigation into how specific characteristics influence the model's decisions. Additionally, future research could focus on reducing the variability in the input data for generating disruption profiles. By narrowing the differences between disruption types, it would be possible to better isolate the model's behavior and achieve more consistent and robust results.

The first approach would help identify targeted mitigation strategies for specific disruption conditions, such as long disruptions or higher reductions in capacity. This would enable agribusinesses to develop strategies according to common disruption patterns in their operations. The second approach would help reduce the variability in results, providing more reliable insights for decision-making.

Chapter 5

Conclusion

This dissertation applies OR methods to address critical challenges in U.S. agricultural supply chains, with a particular focus on disrupting labor trafficking networks in unethical supply chains and mitigating operational disruptions in ethical supply chains. The first research presented in this dissertation highlights the need for targeted strategies to detect labor violations across different states and industries, employing multi-level modeling that provides valuable insights to support anti-trafficking efforts. Secondly, we explore intervention strategies within labor trafficking networks, capturing the dynamic behaviors of trafficking activities in ways that go beyond traditional supply chain models. We evaluate the impact of novel interventions, proposing a new approach to optimize intervention effectiveness in detecting trafficking operations within illicit networks. Lastly, we evaluate mitigation strategies that enhance the resilience of ethical agricultural supply chains under diverse disruptions. Together, these contributions address operational and ethical concerns, supporting the development of resilient and ethically responsive agricultural supply chains.

This research began with a comprehensive analysis of the current inspection strategies used by government agencies to detect labor violations among H-2A workers across states and agricultural sectors. In Chapter 2, we apply a zero-inflated negative binomial model, which provided valuable insights into the distribution of detected H-2A violations. This allows us to identify the states and sectors with frequent reports of violations, as well as areas that showed unexpectedly low or zero counts. Notably, our analysis indicates that the absence of reported violations in certain regions does not necessarily mean no violations have occurred. Our findings identify key characteristics related to detected violations, which can help ensure a more targeted allocation of inspection resources. This approach helps enhance the effectiveness of detecting and enforcing labor violations. Our findings contribute to a more informed inspection strategy that aligns with the specific needs of agricultural regions and industries. They provide government agencies with a data-driven approach to allocate resources where they are needed most, helping to better protect H-2A workers and support fair labor practices.

Chapter 3 advances our understanding of labor trafficking networks by examining how specific interventions can disrupt traffickers' operations within these networks. Our research provides novel insights into the structure and behaviors within trafficking networks, especially the interactions between traffickers and anti-trafficking efforts. We employ a bi-level network interdiction model to evaluate proposed interventions and identify those that are most effective in combating trafficking operations. Our innovative model allows us to analyze twelve targeted interventions, and we utilize k-means clustering to categorize them based on their impact on detection rates. This approach highlights which strategies most effectively alter the network's structure to prevent traffickers from operating undetected. Our analysis also shows that the effectiveness of intervention strategies is influenced by several factors, including the distribution of arcs, the number of echelons affected and their specific disruption impact parameters. These findings provide anti-trafficking stakeholders with a data-driven foundation for selecting and implementing interventions that effectively disrupt trafficking activities within the agricultural sector.

In chapter 4, we develop a scenario-based, multi-period two-stage model that provides a framework for designing supply chains under multiple disruptions, where both primary and backup facilities can be impacted. The model allows for the evaluation of mitigation strategies, such as backup facilities and multi-sourcing, over a defined time horizon. Two disruption distributions were analyzed 90% low-impact and 90% high-impact distributions, representing varying levels of disruption severity and frequency. The results demonstrate that the model employs different cost prioritization strategies depending on the severity of disruptions. In 90% high-impact cases, the model tends to select more backup facilities, allocate higher recovery costs, and achieve lower unsatisfied demand compared to 90% low-impact cases. However, in both situations, the model shows variability in facility selection across ten runs. Further analysis revealed that this variability arises from multiple random factors in disruption scenarios, including random start times, disruption lengths, and capacity reductions. These factors contribute to the challenge of providing consistent facility selection decisions. This study highlights the need for a deeper understanding of how different disruption intensities require varied mitigation strategies. High-impact disruptions, although less frequent, can severely affect facility availability, requiring targeted strategies to address their significant consequences.

5.1 Future Research

Based on the findings of this dissertation, there are several promising areas for further research. Future studies could focus on improving data collection and incorporating technical advancements to enhance the effectiveness of models aimed at disrupting illicit supply chains and strengthening resilience in agricultural supply chains. The following sections outline specific areas for further research that build on these objectives.

5.1.1 Inspection Strategies to Detect Labor Violations among Farm Workers

A significant limitation in detecting labor violations among farm workers is the need for detailed data on essential factors like healthcare access, housing quality, income, and health concerns. While this study highlighted important factors through a comprehensive literature review, there remains a strong need for more in-depth data to understand and fully address labor violations in agriculture. Such data would support future research in developing more targeted inspection strategies and effective approaches to protect farm workers. This study applied a multi level regression model to identify correlations between certain factors and H-2A violation counts, providing a foundation for future research. Building on this work, future studies could investigate causative relationships between these factors and violation counts, offering insights that would be especially valuable for shaping effective policies.

5.1.2 Intervention Strategies to Disrupt Labor Trafficking Networks

A primary constraint is the lack of detailed information on the exact number of individuals affected through the victim's journey from recruitment to exploitation, particularly within the agricultural sector. Addressing this gap is essential for developing more effective and targeted anti-trafficking strategies. To address data limitations, we aggregated information from multiple sources and applied an expert opinion elicitation method to quantify expert assessments into numerical data. Future research could explore the inter-dependencies in the model that were simplified due to limited data on trafficked victims in agriculture. For instance, while we analyzed victim status (e.g., documented, undocumented) independently of housing situations, these factors are likely interconnected. Incorporating these relationships with improved data could enhance the model's accuracy and insights.

For simplicity, we assumed that only one intervention could occur per arc in the network. Future research may consider relaxing this assumption to explore more realistic and complex scenarios. In addition, quantifying how multiple interdictors divide their efforts and the impact of their coordinated interventions is challenging, as their combined actions can either enhance or reduce overall effectiveness depending on their level of collaboration. To address this, we simplified the model by incorporating collaborative interventions into the detailed list, following the assumption that only one intervention can occur per arc. Future work could refine the model by including more detailed data on victim pathways and allowing for multiple interventions per arc. Further research on interdictor collaboration and its impact could improve understanding of intervention effectiveness, enhancing anti-trafficking strategies.

5.1.3 Mitigation Strategies for Enhancing the Resilience of Agricultural Supply Chains

This study considered a constraint where multiple facilities could be disrupted simultaneously, but each facility could experience at most one disruption over the entire time horizon. Relaxing this constraint to allow multiple disruptions at each facility would better reflect real-world disruption patterns and provide deeper insights into the cumulative effects on supply chain resilience.

We also observed variability in the model's results under different disruption sources and intensities, particularly in facility selection and lost sales decisions. This variability arises from the randomness in generating disruption scenarios, which closely mirrors real-world conditions but increases the complexity of decision-making. One potential avenue for exploration is to vary one random factor at a time while keeping others constant to analyze the model's behavior systematically. Another approach could involve narrowing the range of input data while keeping all factors random, reducing variability and enabling a more focused evaluation of the model's decisions.

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Appendix A

Total number of identified H-2A violations per state

This heatmap shows where H-2A program violations were identified in different U.S. states from 2010 to 2020. It includes a range of industries, highlighting where compliance issues with the H-2A program have been found. This information helps reveal patterns in challenges across states and industries.

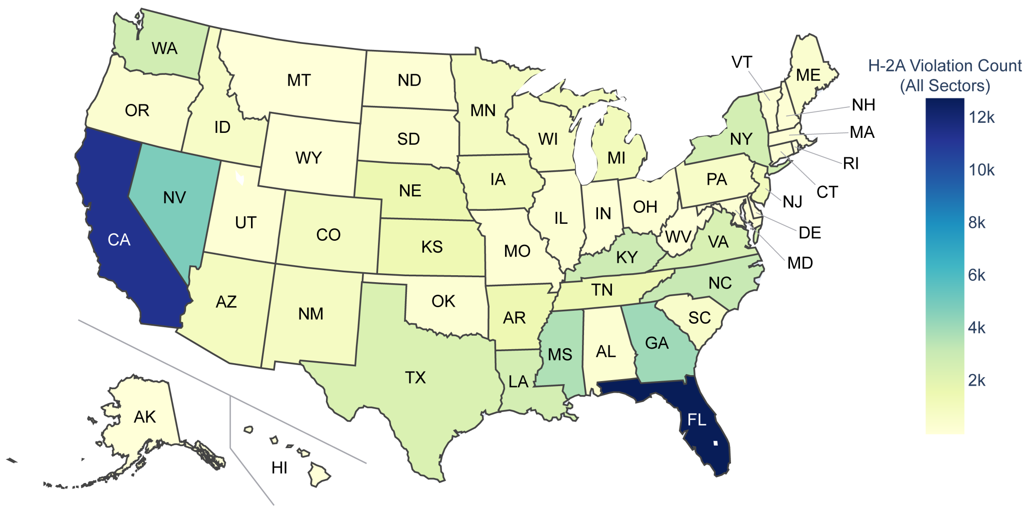

Figure A.1: Geographical overview of H-2A violation counts in all sectors. The heatmap illustrates the total number of identified H-2A violations per state from 2010 - 2020. Note that these violations span various industries, not just those with NAICS codes beginning with "11".

Appendix B

Overview of data on labor trafficking network

Evasion Probabilities and Capacities: Table B.1 displays the the probability of trafficking operations evading detection prior to any additional interventions being taken (p_{ij}) and capacity (u_{ij}) values used in the analysis of Section Result for each node. As mentioned in Section MIN-MAX EVASION NETWORK INTERDICTION MODEL, we use node expansion methods to convert each node in the original network G' to a set of two nodes and an arc in G. This allows us to associate interdictions and input data (including the capacities and evasion probabilities) with the new arc added that represents each original node. Thus, for brevity, we describe the data in the table as it pertains to each original node, with the understanding that this node is converted to an arc when executing the model. Consequently, the capacity and evasion probability for arcs in the original network (which do not correspond to nodes in the transformed network) are set to 1 so that they do not have an effect on the results.

The capacities within the network function to ensure that, in the absence of any interventions, the flow through the network aligns with the current fraction of trafficking operations that use each part of the trafficking network. However, because the flow through the min-max flow network interdiction model represents the overall likelihood of trafficking operations evading detection, the amount of flow is reduced as it progresses through the network. This can be seen in the flow balance constraints (e.g., (4.9) which state that the flow out of a node equals the flow into that node multiplied by (i.e., reduced by) the probability of evading detection at that node. Hence, the outgoing flow will be less than the incoming flow to a node if the corresponding evasion probability is less than 1. As such, to ensure that the flow through the network aligns with the proportion of trafficking operations using each component of the network, we must create capacities u_{ij} so that the resulting flow through nodes in the absence of an intervention occurs in line with the desired proportions from the literature. Let's call these desired proportions $\bar{u}_{ij}$.

No normalization is needed for the first echelon (Recruitment) because constraint (4.46) pushes 100% of the flow into the recruitment nodes; it has not yet been reduced by the evasion probabilities. Thus, the capacities for the recruitment echelon are set equal to the proportions from the literature ($u_{ij} = \bar{u}_{ij}$).

All other echelons require normalizing the capacities. We explain our process using the Status echelon as an example; the capacities for the other echelons can be calculated similarly. The maximum amount of flow possible out of the recruitment echelon and into the status echelon equals the sum product of the recruitment node capacities and the evasion probabilities (i.e., from Table B.1: $0.02 * 0.9 + 0.03 * 0.96 + ... + 0.05 * 0.81 = 0.909$). Thus, the total amount of flow that could go into the Status echelon is 0.909%. We wish to normalize this flow by the proportion of trafficking operations whose victims are in-status, have no U.S. status, and are U.S. citizens. We assumed from the literature that 30% of agricultural labor trafficking trafficking victims are in status, 60% have no U.S. status, and 10% are U.S. Citizens. Therefore, the resulting capacities for the Status become:

$\bar{u}_{In-status}$: $0.3 * 0.909 = 0.27$

$\bar{u}_{NoU.S.Status}$: $0.6 * 0.909 = 0.55$

$\bar{u}_{USACitizen}$: $0.1 * 0.909 = 0.09$

We estimated the input data $\theta_{ij}^{d\omega}$ using the perception of probabilities, explained in Section DATA AND INTERVENTIONS. The parameters $\theta^{d,low}$ and $\theta^{d,high}$, presented in Table B.2, indicate the average values of $\theta_{ij}^{d\omega}$ for each arc under each intervention, categorized into low and high impact scenarios.

Probability of scenarios – The scenario generation process begins once interdictors choose an intervention strategy. This involves defining the specific interventions and the arcs they affect. The number of potential scenarios depends on whether the interventions have low or high impacts. To determine the probability of each scenario, we used the parameter $\theta^{d,\omega}$, represented in Table B.2. This parameter reflects the likelihood of low and high impacts on the network arcs under different scenarios.

Imagine interdictor(s) select interventions A and B, which can affect certain arcs in the network with varying probabilities. Each intervention has a probability of impacting an arc (i, j)

under a specific scenario ω, denoted as $\theta_{ij}^{f\omega d}$. Since each intervention can affect multiple arcs, we calculate the average of $\theta_{ij}^{f\omega d}$ across all arcs impacted by intervention d, separately for low and high impacts. This results in an aggregated parameter $\theta_{avg}^{f\omega d}$ for each level of impact. The uncertainty in the impact of interventions creates multiple possible scenarios. Each scenario represents a specific combination of low and high impacts across all interventions, as detailed in Table B.3. Consequently, the total number of possible scenarios is given by $2^{\sum_{d \in D} X_d}$, where each intervention d can either have a low or high impact. For example, with two interventions, A and B, each having the potential for either low or high impact, the total number of scenarios is $2^2 = 4$.

To determine the probability of each scenario, we assume it can be derived as the product of the average probabilities $\theta_{avg}^{f\omega d}$ for the selected interventions. Specifically, for the second scenario where intervention A has a low impact and intervention B has a high impact, the probability of this scenario is calculated as $\theta_{avg}^{low,2,A} \times \theta_{avg}^{high,2,B}$, please see Table B.3. This approach allows us to estimate the likelihood of each scenario by combining the independent probabilities of the impacts from all selected interventions.

Table B.1: The pre-intervention evasion probability and capacity data used as input into the network interdiction model

Node	**Pre-Intervention Evasion Probability** (p_{ij})	**Capacity** (u_{ij})
Force	0.90	0.02
Fraud	0.96	0.03
Coercion	0.96	0.03
Fees	0.95	0.02
Force/Fraud	0.87	0.07
Force/Coercion	0.89	0.07
Force/Fees	0.86	0.06
Fraud/Coercion	0.95	0.2
Fraud/Fees	0.93	0.10
Coercion/Fees	0.95	0.10
Force/Fraud/Coercion	0.86	0.05
Force/Fraud/Fees	0.83	0.04
Force/Coercion/Fees	0.85	0.04
Fraud/Coercion/Fees	0.92	0.12
F/F/C/F	0.81	0.05
In-status	0.92	0.2726
No U.S. status	0.98	0.5451
Citizen	0.94	0.0909
BC land	0.95	0.139
BC Air	0.92	0.078
BC Sea	0.95	0.026
No BC needed	0.99	0.174
Unofficial crossing	0.96	0.453
Employer-owned housing	0.95	0.376
Employer-facilitated housing	0.96	0.250
Third-Party housing	0.94	0.2090
Work hour	0.96	0.0159
Wage	0.94	0.0159
Mental abuse	0.96	0.0238
Physical abuse	0.87	0.0238
Work Hour/wage	0.91	0.0318
Work Hour/mental Abuse	0.95	0.0636
Work Hour/Physical Abuse	0.84	0.0636
Wage/mental Abuse	0.93	0.0795
Wage/physical Abuse	0.82	0.0795
Mental Abuse/Physical Abuse	0.86	0.159
Work Hour/wage/mental	0.90	0.0397
Work Hour/wage/physical	0.76	0.0397
Work Hour/mental/physical	0.80	0.0477
Wage/mental/physical	0.78	0.0715
WH/W/M/P	0.75	0.0397

Table B.2: The table shows the post-intervention evasion probabilities and the likelihood that each intervention has high impact and low impact.

Intervention ID	$\theta^{d,low}$	$\theta^{d,high}$	$q_{ij}^{d,low}$	$q_{ij}^{d,high}$
d1	74%	26%	2%	12%
d2	50%	50%	3%	13%
d3	50%	50%	7%	17%
d4	37%	63%	6%	16%
d5	90%	10%	0.35%	3.5%
d6	50%	50%	0.35%	3.5%
d7	90%	10%	2%	12%
d8	56%	44%	1.25%	3.75%
d9	70%	30%	2%	12%
d10	74%	26%	9%	18%
d11	90%	10%	8%	18%
d12	38%	62%	10%	20%

Table B.3: Scenario generation and probabilities

Scenario	Intervention A	Intervention B	Probability
1	low	low	$\phi_1 = \theta^{A,1,low} \times \theta^{B,1,low}$
2	low	high	$\phi_2 = \theta^{A,2,low} \times \theta^{B,2,high}$
3	high	low	$\phi_3 = \theta^{A,3,high} \times \theta^{B,3,low}$
4	high	high	$\phi_4 = \theta^{A,4,high} \times \theta^{B,4,high}$