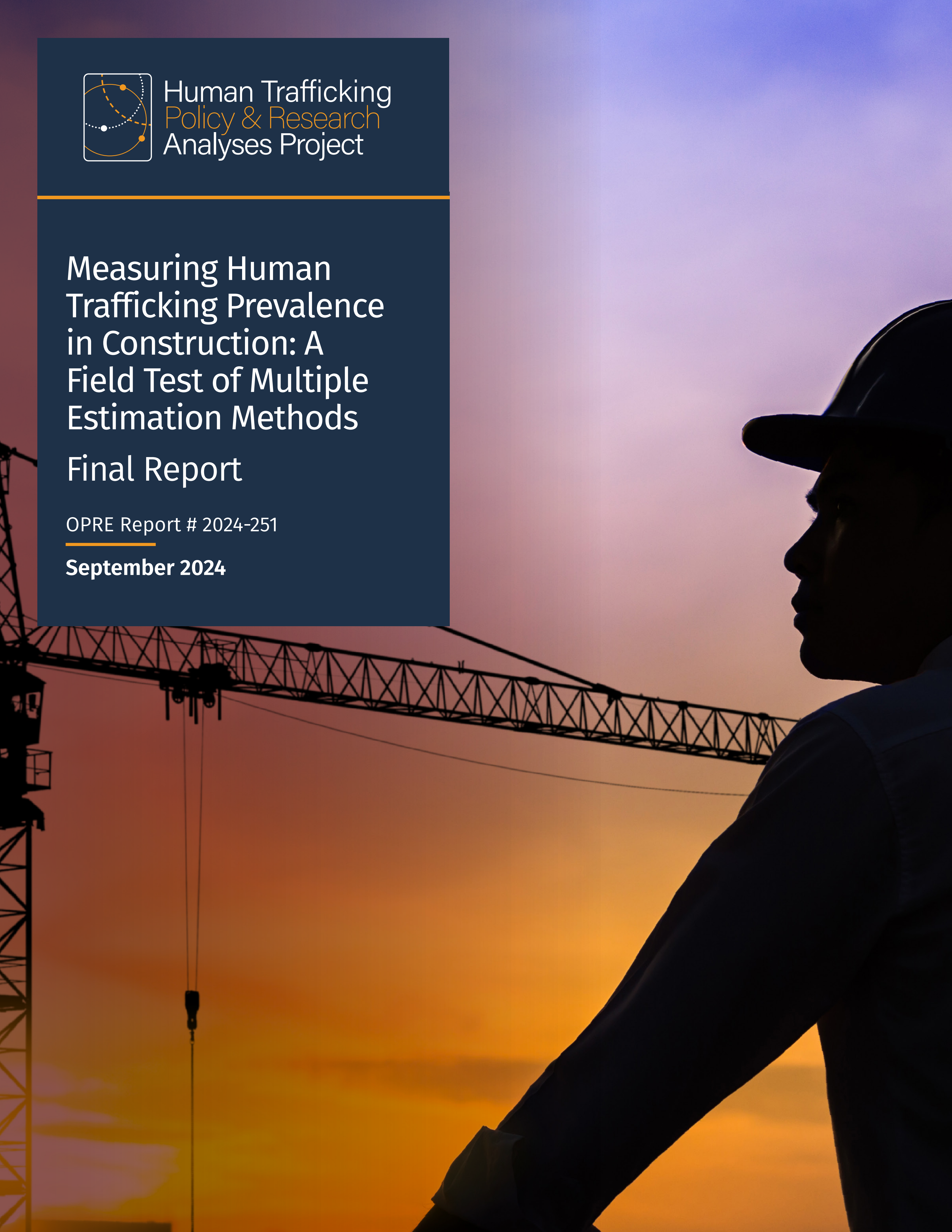
Human Trafficking
Policy & Research
Analyses Project

Measuring Human Trafficking Prevalence in Construction: A Field Test of Multiple Estimation Methods

Final Report

OPRE Report # 2024-251

September 2024



Measuring Human Trafficking Prevalence in Construction: A Field Test of Multiple Estimation Methods

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LIST OF EXHIBITS

One goal of the Human Trafficking Policy and Research Analyses Project is to **advance knowledge of promising methods for estimating human trafficking prevalence in the United States.**

To accomplish this, RTI International is undertaking a focused prevalence inquiry of human trafficking in the nation. The inquiry will involve the application of two rigorous sampling methods to estimate the prevalence of trafficking victimization in one U.S. industry and one U.S. location.

OVERVIEW

Introduction

To advance knowledge about promising methods for estimating the prevalence of human trafficking in the United States, the Administration for Children and Families' Office of Planning, Research, and Evaluation (OPRE) and the Office on Trafficking in Persons (OTIP) funded a study, conducted by RTI International, to field test two methods of prevalence estimation within one industry in one geographic location in the United States.

This study, conducted between 2020 and 2024, measured the prevalence of labor trafficking within the construction industry in Houston, Texas, using both time-location sampling (TLS) and link-tracing sampling (LTS). TLS involves developing a sampling frame of venues, days, and times where the population of focus congregates and using a random selection procedure (e.g., every fifth person) to select a representative sample of the population. LTS is a network sampling approach that relies on study participants to recruit their peers to participate in the study.

Primary Research Questions

- How do the number and characteristics of construction workers who self-reported exploitation and trafficking experiences compare by prevalence estimation strategy?
- What is the nature and type of exploitation experienced by construction workers?
- What are the potential risk and protective factors associated with trafficking victimization?

Purpose

This final report summarizes the human trafficking prevalence estimates generated by both the TLS and LTS strategies. Additionally, the report describes the nature and types of experiences with both labor trafficking and other labor exploitation that does not meet the threshold of labor trafficking among construction workers included in the study sample and explores patterns in risk and protective factors associated with human trafficking victimization.

Methods

Study findings are informed by the results of 1,427 surveys, taken by construction workers identified through either TLS or LTS sampling. The survey included measures of workplace exploitation as well as demographic information about respondents and their employment situations and experiences. In total, 903 construction workers were recruited through TLS, and 524 construction workers were recruited through LTS. Data collection occurred between August 2022 and August 2023.

Key Findings and Highlights

- Data collection and prevalence estimation strategies matter. Although both TLS and LTS are promising approaches for identifying and recruiting construction workers, only TLS proved to be effective in reaching the population.
- TLS was a more effective sampling strategy than LTS. Surveyed construction workers were hesitant to refer their peers for the survey, resulting in few referrals and limiting our ability to generalize results from the LTS sample to a broader sample of construction workers in Houston.
- Results from the TLS sample indicate that 22% of construction workers in Houston have experienced labor trafficking in their lifetime, 13% have experienced labor trafficking within the past 2 years, and 4% have experienced or are experiencing labor trafficking in their current job.
- Although individual characteristics and employment experiences were assessed as potential risk and protective factors, only one significant difference emerged: Construction workers who have worked in clean-up and reconstruction efforts after a natural disaster are more likely to have experienced labor trafficking and other labor exploitation than those who have not worked in the aftermath of natural disasters.

EXECUTIVE SUMMARY

Study Overview

Central to decisions among policymakers, funders, and researchers concerned with addressing human trafficking is the question of the size of the problem. Understandably, these groups seek evidence about the prevalence of human trafficking to guide choices around policies and interventions to prevent and address human trafficking in communities. Several empirical efforts have been established in recent years in response to this quandary, including a series of seven studies included in the Prevalence Reduction Innovation Forum (PRIF) initiative (Center on Human Trafficking Research & Outreach, n.d.), which aims to build evidence about methodologies to estimate the prevalence of human trafficking by testing various estimation methods in various industries in six other countries. In each of these seven studies, two estimation strategies are used to estimate the prevalence of human trafficking among a certain population in a certain area. This dual estimation approach offers insight about both (1) the logistics and feasibility of carrying out each estimation strategy and (2) how the prevalence estimates that they generate compare to one another.

The current study was designed as a domestic counterpart to the seven international PRIF studies. Following a comprehensive review of prior human trafficking prevalence studies (see Barrick & Pfeffer, 2021) and a consideration of factors such as industries of identified interest and feasibility of estimation strategies, we chose to focus this study on the prevalence of labor trafficking within the construction industry in Houston, Texas, using both time-location sampling (TLS) and link-tracing sampling (LTS). TLS involves developing a sampling frame of venues, days, and times where the population of focus congregates and using a random selection procedure (e.g., every fifth person) to select a representative sample of the population. LTS is a network sampling approach that relies on study participants to recruit their peers to participate in the study.

The objectives of the study were to advance knowledge of promising methods for estimating human trafficking prevalence and to better understand substantive issues around the experiences of construction workers with labor trafficking and other labor exploitation.

The survey instrument was developed using guidance from PRIF to address three main research questions:

1. How do the number and characteristics of construction workers who self-reported exploitation and trafficking experiences compare by prevalence estimation strategy (TLS vs. LTS)?
2. What is the nature and type of exploitation experienced by construction workers?
3. What are the potential risk and protective factors associated with trafficking victimization?

Study participants were asked about a range of trafficking indicators. If they responded to any affirmatively, they were asked a series of follow-up questions to understand how recently the exploitation occurred and whether it occurred in recovery or reconstruction work following a natural disaster. We used a statistical definition developed by PRIF, which provides guidance to determine whether participants had experienced (1) labor trafficking, (2) other labor abuse not meeting the threshold of labor trafficking, or (3) no exploitative work experiences in their work in the construction industry.

This study relied on bilingual field interviewers to administer a web-based survey on tablets, and participants were compensated with a $50 gift card for their participation. This study included 1,427 construction workers. The TLS sample included 903 participants, and the LTS sample included 524 participants.

Study Findings

The LTS sample did not yield a high response rate, and we only include high-level findings from this sample in this report. Even with financial incentive, workers were hesitant to refer their peers to participate in this study, and relatively few referral chains developed. Given the limited number of chains available for analysis and the potential for misleading findings, LTS sample findings are only presented to highlight differences in prevalence estimation strategies.

More than one in five construction workers had experienced labor trafficking victimization in their lifetime. Among the TLS sample (n = 903), 22.3% had experienced labor trafficking in construction in their lifetime, 13.2% had experienced labor trafficking within the past 2 years, and 4.2% had experienced or were experiencing labor trafficking in their current job.

An additional 42% of construction workers reported experiencing other labor abuses that did not meet the threshold of labor trafficking. Just over one third (35%) of workers had never experienced any labor trafficking or exploitation in the construction industry.

Although individual characteristics were assessed as potential risk and protective factors, no significant differences emerged. Given the limited extant research focusing on risk and protective factors for experiencing labor trafficking or other labor abuse in construction, additional work is needed to substantiate the lack of significant findings regarding individual characteristics.

Construction work related to natural disaster recovery and reconstruction is associated with a higher prevalence of labor trafficking and other forms of labor abuse. Construction workers who had worked in natural disaster recovery and reconstruction settings were significantly more likely than those who had not to have experienced labor trafficking or other labor abuse.

Conclusions and Implications

Labor trafficking and other labor abuse in the construction industry are common. About two-thirds of Houston construction workers experienced at least one form of exploitative or abusive labor practice. The types of abuse most frequently experienced by construction workers include working without a contract, deception about working and living conditions, working long and unusual hours without adequate compensation, and paying recruitment fees to get a job. However, nontrivial percentages of construction workers were subjected to more serious forms of abuse, including having their pay withheld, deception about the work they would be doing, and being subjected to emotional or psychological abuse. These findings have implications for policymakers, law enforcement, Departments of Labor and other regulatory agencies, construction unions, workers' advocacy groups, and anyone concerned about workplace exploitation in the construction industry.

Related to prevalence estimation methodologies, we confirmed that data collection and prevalence estimation strategies matter. Although both TLS and LTS are promising approaches for identifying and recruiting construction workers, only TLS proved to be effective in reaching the population. All prevalence estimation research should clearly highlight challenges that occurred during data collection that may impact the validity of the findings and exercise caution in reporting potentially misleading estimates.

INTRODUCTION

As part of the Administration for Children and Families' (ACF's) Human Trafficking Policy and Research Analyses Project (HTPRAP), RTI undertook a focused prevalence inquiry of human trafficking in the United States. The overarching goal of this project was to advance knowledge of promising methods for estimating human trafficking prevalence in the United States by field testing at least two methods of prevalence estimation within one industry in one geographic location in the United States.

Human trafficking is a hidden crime, and lack of empirical data on the scope of the problem limits efforts to disrupt trafficking and meet the needs of those who have been exploited. Without empirical data, prevention and intervention efforts will be driven by an inaccurate understanding of the magnitude of the problem, potentially resulting in either too little or too much intervention. In recent years, demand for accurate estimates of the prevalence of human trafficking has increased (e.g., Executive Order 13903 [Office of the Federal Register, National Archives and Records Administration, 2020]), and federal agencies have acted by convening workshops examining challenges to and strategies for measuring the prevalence of sex and labor trafficking (NAS, 2020) and developing initiatives focused on improving approaches to estimate prevalence. One such initiative, the Prevalence Reduction Innovation Forum (PRIF) (Center on Human Trafficking Research & Outreach, n.d.), was funded by the State Department's Office to Monitor and Combat Trafficking in Persons to build evidence about methodologies to estimate the prevalence of human trafficking by testing different estimation methods in various industries in six other countries. Each of these projects involved field testing at least two different prevalence estimation methods. ACF's

Office of Planning, Research, and Evaluation (OPRE) and Office on Trafficking in Persons (OTIP) funded this project to serve as the domestic counterpart to these studies.

For more information about our review of prior human trafficking prevalence studies and our procedure for selecting an industry and geographic location of focus for this study, please see the Comprehensive Review of Prior Prevalence Studies and Recommendations for Field Testing in the United States report.

An initial step in this project was to select the industry, estimation methods, and geographic location on which to focus. To inform these decisions, the team (1) conducted a comprehensive review of prior human trafficking prevalence studies, focusing primarily on the sampling and estimation strategies that have been successfully used in prior research; (2) assessed the strengths and weaknesses of the main prevalence sampling methods for estimating trafficking; (3) considered how well each method could be used in different industries; and (4) developed recommendations for field-testing prevalence estimation strategies in the United States (Barrick & Pfeffer, 2021; 2024). Our labor sectors of consideration were guided by those specifically indicated as priority areas by OTIP in the workshop *Estimating the Prevalence of Human Trafficking in the United States: Considerations and Complexities*, hosted by the National Academies of Sciences, Engineering, and Medicine on February 25, 2020:

- Direct care workers, including personal care aides, home health aides, and nursing assistants, in private homes, communities, and nursing homes
- Childcare workers
- Animal husbandry, including on chicken, egg, and dairy farms
- Construction, including roofing, carpentry, welding, electrical work, and debris removal (particularly after natural disasters)
- Illicit activities, particularly through forced labor among juveniles in domestic gang activity

In summary, our review of the research found that prior prevalence studies used a variety of sampling and estimation strategies, including traditional probability samples (e.g., multistage, stratified, cluster), variants of multiple systems estimation and capture-recapture techniques, respondent-driven sampling and related link-tracing sampling (LTS), and other novel approaches. For survey-based approaches to estimating prevalence, traditional probability samples have included large-scale household- and school-based surveys; respondent-driven sampling and LTS have been used to develop samples of specific populations in smaller geographic areas; and time-location sampling (TLS) has been used to recruit youths to study child labor. When adequate administrative data or records on individuals who have experienced trafficking are available, multiple systems estimation or capture-recapture techniques have been used in lieu of survey approaches (e.g., Bales, Hesketh & Silverman, 2015; Chan, Silverman, & Vincent, 2021). Because administrative data on labor trafficking victimization are generally lacking, we determined that a survey approach was needed for this study.

From a planning perspective, the labor sector in which the prevalence study is to be carried out is the most critical factor. Whenever survey data are needed, access to the prospective population affects which recruitment methods are feasible. We believed that the most practical labor sector to target for this project was the construction industry because the work largely occurs in outdoor, accessible settings, and construction sites are also typically known[1] by and registered with municipalities. Based on our analysis of the strengths and weaknesses of prevalence estimation strategies and how well each method would work for construction, we recommended that our targeted prevalence study use traditional probability sampling and LTS methodologies to estimate the prevalence of labor trafficking victimization in the construction industry. We originally envisioned that the probability sample would involve a geographic sampling approach, such as developing, through a grid-type sampling approach, a map of all existing construction sites for a given geographic location. In this design, a grid would be applied to a map of the entire geographic location, and pieces of the grid would be randomly selected for inclusion in the study. For LTS, we initially planned either to use the probability-based sample to find seed participants or to partner with unions or other advocacy groups in the area to identify seed participants who are employed by different contractors in the area.

One of the priorities with construction was to assess the extent of trafficking after a natural disaster. Although it is impossible to plan a study around a future disaster, some disasters, such as hurricanes, occur fairly frequently and repeatedly impact the same communities. This approach resulted in two key considerations for selecting a site: (1) a large construction industry so we would have enough workers to survey and (2) frequent severe disasters so we could gather information about labor abuses that occur in the clean-up and rebuilding after a disaster. We first decided to focus on hurricanes as the disaster type because they are more predictable than other types of disasters and tend to cause substantial damage that requires a large reconstruction effort. We then developed a list of communities that rated high on a hurricane risk index, which accounts for both population density and hurricane frequency (Hurricane Risk Index, n.d.). We then extracted Census data on the size of the construction industries in these communities (U.S. Census Bureau, 2018). We selected Houston because it has an extremely large construction industry and was rated high on a hurricane risk index.

After Houston was selected to serve as the study site, we found that lists of current, permitted construction sites were publicly available via a Texas Public Information Act request. Given the availability of this sampling frame, we revisited our preliminary plans to use a geographic sampling approach. We determined that we could develop a TLS sample using these lists of permitted construction sites, which involved developing a sampling frame of venues, days, and times based on a list of venues crossed with days and time slots for potential observation where the target population congregates (i.e., construction sites). Next, we used a random

[1] Although permits are required for construction, they are not always pulled.

selection procedure to select a venue-day-time slot and then a systematic procedure (e.g., every fifth person) to select a probability sample of the population. We did not initially recommend TLS because construction workers are dispersed broadly across communities, and we did not anticipate that they would frequent certain venues or that they would be visually distinguishable from other types of workers. However, the ability to sample individual construction sites as the venue removed this obstacle. We selected a TLS design that relies on a probability-based sample of permitted construction sites to recruit current workers. Potential time intervals for recruitment were added to the probability-based sampling frame of permitted construction sites. This approach is described in detail in the **Time-Location Sampling section**.

In addition to advancing knowledge of promising methods for estimating prevalence, we also sought to explore substantive issues around the labor trafficking of construction workers, including the nature of the exploitation and the risk and protective factors for victimization. These guiding research questions are summarized in **Exhibit 1**.

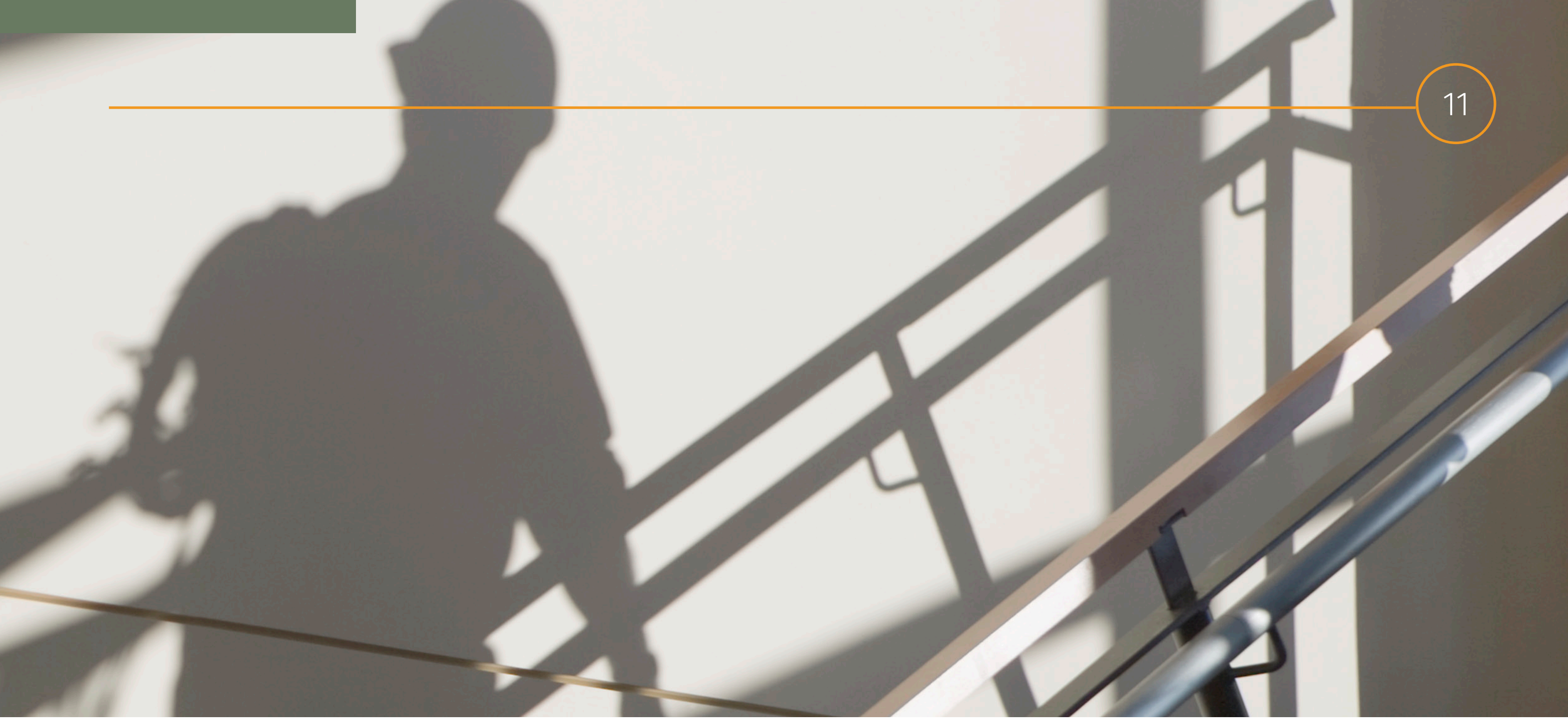
Exhibit 1. Research Questions

RQ1: How do the number and characteristics of construction workers who self-reported exploitation and trafficking experiences compare by prevalence estimation strategy?	
RQ1a	How many and what percentage of construction workers in the study site have experienced labor exploitation and trafficking?
RQ2: What is the nature and type of exploitation experienced by construction workers?	
RQ2a	What types of exploitation were experienced by construction workers during recruitment (e.g., coercion, deception, fees)?
RQ2b	What types of exploitative employment practices and penalties were experienced by construction workers (e.g., pay withheld, made to perform additional services or responsibilities, unpaid overtime)?
RQ2c	How do employers treat the personal life and property of construction workers (e.g., control over a meaningful part of someone’s life, confiscation of mobile phones)?
RQ2d	What types of degrading conditions were experienced by construction workers?
RQ2e	To what extent was the freedom of movement or the communication of construction workers restricted (e.g., identification documents confiscated, surveillance, and monitoring)?
RQ2f	What forms of debt or dependency were experienced by construction workers?
RQ2g	What forms of violence (or threats of violence) were experienced by construction workers?
RQ3: What are the potential risk and protective factors associated with trafficking victimization?	
RQ3a	What individual-level factors (e.g., gender, national origin, English proficiency) differentiate construction workers who report trafficking experiences from other workers?
RQ3b	What employment characteristics (e.g., construction work during natural disaster recovery, type of construction work, length of employment in construction, methods for finding work in construction) differentiate construction workers who report trafficking experiences from other workers?

RESEARCH METHODS AND ANALYTIC STRATEGY

INSTRUMENTATION

The survey instrument was developed using guidance from PRIF to address the three main research questions. Most of the survey instrument focused on **Research Questions 1** and **2** and solicited information on the nature and type of exploitation experienced. This information is used to describe the prevalence of trafficking and the nature and type of exploitation construction workers experience. Demographic information was collected to describe and measure the correlation between experiencing trafficking and the characteristics of construction workers. Human trafficking is difficult to define and measure. Most crimes, like burglary and car theft, are defined by individual incidents. For example, if someone breaks into your house and steals something, you have been burglarized. However, human trafficking may involve a series of incidents over time, and there is no standard threshold for determining when these events become trafficking. Although the United Nations adopted an international protocol for defining trafficking in persons in 2000, differences in national and state definitions remain. Moreover, individual research studies often differ in how they measure trafficking victimization, and some definitions do not align with established legal definitions. The questions used to estimate the prevalence and describe the nature of labor exploitation and trafficking were adapted from a set of items developed by PRIF, which developed a statistical definition of human trafficking to guide the research teams who are leading these studies (PRIF, 2020). All teams were expected to select the most relevant indicators for their population and to adapt the language as needed to fit the industry of focus and the cultural context. The PRIF statistical definition served as the foundation for our survey instrument. The definition includes a series of trafficking indicators across various domains (see sidebar). Each item was assigned a severity level of either medium or strong. **Exhibit 2** presents examples of the types of indicators that fall into each category and severity level (full instrument available in the **Appendix**).



Categories of Trafficking Indicators

- Recruitment
- Employment practices and penalties
- Personal life and properties
- Degrading conditions
- Freedom of movement
- Violence and threats of violence
- Debt or dependency

Study participants were asked whether they had ever experienced each of the trafficking indicators. If they had, they were asked a series of follow-up questions to assess how recently the exploitation occurred (i.e., within the past 2 years or currently) and whether it happened in the recovery from a hurricane or other natural disaster. Workers' responses to these questions were used to determine whether they had experienced labor trafficking. The PRIF statistical definition provided thresholds that distinguish trafficking from other forms of labor abuse by accounting for both the severity and the number of types of exploitation that an individual experienced. An individual was coded as having experienced trafficking if they met one or more of the following criteria:

- They indicated experiencing a lack of freedom of movement or communication.
- They indicated experiencing two or more strong trafficking indicators from different categories.
- They indicated experiencing one strong indicator and at least three medium indicators in any category.

Trafficking victimization was also measured over the lifetime (ever met threshold) and in two other timeframes specified in the PRIF statistical definition: flow (number of victims of trafficking who met threshold during a specific period of time, defined here as within the past 2 years) and stock (number of individuals who currently meet threshold, defined here as in the respondent's current employment situation) (PRIF, 2020).

The survey also included items on potential risk and protective factors to address Research Question 3. Topics included professional background and personal demographics and were developed based on a review of published labor trafficking studies (Zhang et al., 2014; 2019). Personal-level factors included age, race, ethnicity, gender, national origin, English proficiency, educational attainment, marital status, and physical or cognitive disability. Employment-level factors included current employment status, experience working during the recovery and reconstruction efforts after natural disasters, length of time in the construction industry, strategies used to find work, and type of construction work. At the conclusion of the survey, respondents were provided links to resources, including the National Human Trafficking Hotline and local worker rights/justice organizations.

To allow increased flexibility for when and where the survey could be completed, the instrument was developed as a web-based survey. The field team was equipped with a tablet with a cellular signal so they could administer the survey to workers at construction sites. Alternatively, workers could self-administer the survey at another time on any device with internet capabilities and access.

Exhibit 2. Example Indicators, by Category and Severity Level

Category	Medium Severity	Strong Severity
Recruitment	Sometimes people pay money to help get a job. Have you or has anyone ever paid a recruitment fee or a broker fee to help you get a job?	Sometimes lies are used to trick people into accepting a job. Have you ever felt cheated or lied to about the nature of your job or specific responsibilities of the work you were supposed to do?
Employment practices and penalties	Have you ever been made to perform additional or specialized services (beyond what was agreed beforehand) without being paid appropriately?	Sometimes people work for employers who do not let them leave their jobs. Has your employer or people who work for your employer withheld your pay and/or benefits to prevent you from leaving or told you that you would lose your pay already earned if you decided to quit?
Personal life and property	Sometimes employers may not want workers to use mobile phones or other personal devices outside of working hours. Have you ever had your mobile phone or other device taken by your employer or people who work for your employer outside of working hours?	Sometimes employers want to have control over people's lives outside their job. Has your employer or people who work for your employer ever attempted to control your personal life outside of work?
Degrading conditions	Has your employer or people who work for your employer asked you to do dangerous work without proper protective gear?	Has your employer ever required that you work longer than normal hours, unusually long days, or outside of normal working hours without being properly compensated for overtime?
Freedom of movement	Have you ever experienced any limitations on your movement or communication, such as having employers supervise or listen in on your communication or restrict or monitor your movement during hours when you were not working?	Has your employer or people who work for your employer ever taken/confiscated your identity papers (such as passport, work permit) or made it so that you were you unable to access your identity papers?
Debt or dependency	N/A	Have you ever had a debt imposed on you without your consent? For instance, has your employer decided that you owed them money for reasons you didn't agree with (e.g., pay for things that were not part of your work agreement)?
Violence or threat of violence	Has your employer ever threatened physical violence against you?	Has your employer ever used physical violence against you?

SAMPLING AND ESTIMATION STRATEGIES

Study participants were sampled and recruited through two strategies: TLS and LTS. The goal was to generate separate prevalence estimates from each of these samples. The rest of this section details the original sampling plans and challenges that were encountered in the field.

Time-Location Sampling

TLS involves developing a sampling frame of venues, days, and times where the target population congregates and using a random selection procedure (e.g., every fifth person) to select a representative sample of the population. This was deemed a promising method to use among construction workers because they congregate at worksites at predictable time intervals where they can be identified and recruited to participate. In Texas, lists of permitted construction sites are available through a public information request. Lists were requested monthly, and sites served as the "venue" for sampling frame. The city was broken into 12 regions, and sites were sampled, by simple random sampling, from one region per month, every month, for a year. Permitted sites were randomly selected and assigned hour-long windows for field staff to visit those sites. Although permits are required for construction, they are not always pulled. To capture nonpermitted construction sites, the team also canvassed blocks surrounding the selected sites to identify other visible construction sites that were not sampled. The construction sites that were visited for the TLS sample were mostly residential construction (e.g., townhomes, single-family homes), with some commercial buildings (e.g., large pieces of land where a new building was being constructed, high-rises).[2]

Field interviewers (FIs) approached workers at each site, screened them for eligibility, and administered the web-based survey on a tablet. Administration occurred in three ways, depending on each participant's preference: (1) the participant self-administered the survey on the tablet, (2) the FI administered the survey by reading the questions and response options to the participant verbatim, or (3) the FI provided the worker with information to complete the survey later on a personal device. The survey took approximately 10–20 minutes to complete. Participants were provided with their choice of a physical or electronic $50 gift card for their participation.

The team encountered several challenges that required minor deviations from the original data collection plan. Although the permit list included both residential and commercial construction, the sample primarily consisted of small sites, such as residential home construction and repair or remodeling tasks (e.g., installing a fence). Because these jobs can often be accomplished fairly quickly, workers were often not present during the day-time slots sampled for the site. Even when workers were present, there were fewer workers than anticipated under the assumption that some sites would involve larger, commercial construction projects. The project team monitored data collection closely to adjust for any changes with the TLS sample, particularly in the beginning of the project. We began by sampling 50 sites for the first 6 weeks and surveying every fourth worker for a maximum of four workers per site. By the end of data collection, we sampled up to 300 sites per month with no constraint on the *nth* worker (i.e., any present worker was eligible) for a maximum of four workers per site.

In total, the TLS sample included 903 construction workers.

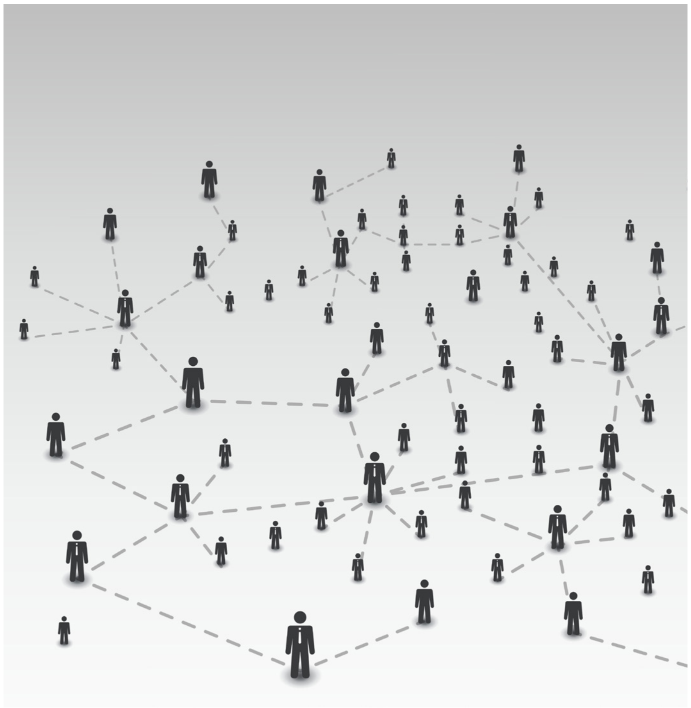
[2] In 2022, over 24,000 employees were involved in the construction of buildings (residential and commercial) in Harris County, Texas (U.S Census Bureau, 2022).

Link-Tracing Sampling

LTS was used to supplement the TLS sample. LTS is a network sampling approach that relies on study participants to recruit their peers to participate in the study. LTS is similar to respondent-driven sampling (RDS), which has been used successfully in studies to estimate the prevalence of sex trafficking (e.g., Dank et al., 2019; Jordan et al., 2020) and labor trafficking of undocumented immigrants (Zhang et al., 2014). LTS is a promising method to use among construction workers because they often work in groups and have regular contact with other construction workers who may be eligible to participate in the study. The peer recruitment process starts by selecting a set of initial participants (i.e., seeds) who complete the survey and then invite their eligible peers to participate. Seeds included members of the TLS sample and additional respondents recruited at locations where day laborers congregate (e.g., Home Depot, gas stations). Much like the TLS sample, the project team monitored data collection closely to adjust for any needed changes. We began by inviting every third worker to be the seed. By the end of data collection, every second worker was the seed. Like the TLS sample, all seeds were provided the option of a physical or electronic $50 gift card for completing the survey. The seeds were then allowed to invite up to three eligible peers to participate, each of whom could also invite up to three peers. At the end of the survey, participants were asked whether they would be willing to provide contact information (phone or email) for friends or family they knew that also worked in construction in the past 2 years. If they agreed, participants entered the information for up to three peers. Participants were provided a $25 electronic gift card for each referral (up to a maximum of $75 for three peers) who completed the survey. Because the referral process occurred without the FI present, a physical gift card was not an option, and participants were required to enter their email address to receive the incentive for completing the survey.

Few seeds in the LTS sample successfully recruited a peer to complete the survey. Because the success of this sampling strategy relies on peer referrals, only sample characteristics and high-level prevalence estimates from the LTS sample are presented to highlight methodological differences.

The LTS sample did not yield a high response rate, primarily because workers were hesitant to refer their peers to participate in the study. This hesitance could be due to a lack of trust with providing their peer's contact information or a poor experience completing the survey (i.e., they did not want to make their peers go through it). The initial seed participants also indicated preferring a physical gift card for their referral compensation, which was not an option given the study design. Even when referrals were made, few workers completed the survey, suggesting that having the FI explain the purpose of the survey in person was important for recruitment. In total, 524 individuals were in the LTS sample, but only 262 were included in the analysis due to the lack of referrals; 319 seed participants provided referrals, and 57 were removed from the LTS sample to avoid duplication because they were already in the TLS sample (members of the TLS sample were also invited to recruit peers to participate). However, because few seeds recruited a peer in the current study, only limited findings from the LTS sample are presented.



TLS ANALYTIC STRATEGY

The outcome measures were the PRIF definition criteria for the three periods of victimization, labeled lifetime, past 2 years, and current job. Analyses included calculating weighted means and proportions using survey weights to adjust for the sampling design. Proportions were then multiplied by 100 to convert them into percentages, as reported in the **Findings section**. Sampling weights were calculated as the inverse product of two-stage selection probabilities using the Horvitz-Thompson estimator for TLS samples following the approach of Leon et al. (2015). Leon et al. describe a three-stage TLS estimator wherein the first stage was the selection of locations. In the current study, all zones were visited (i.e., we did not subsample zones) and thus have equal probabilities, reducing our implementation of the Horvitz-Thompson TLS estimator to two stages: the selection of sites within geographies and the selection of workers within each site. The probability of selecting a site within a geography was calculated as the number of selected sites divided by the number of permitted sites available to visit. The probability of worker selection was 1/n where every *nth* worker was selected, as previously described.

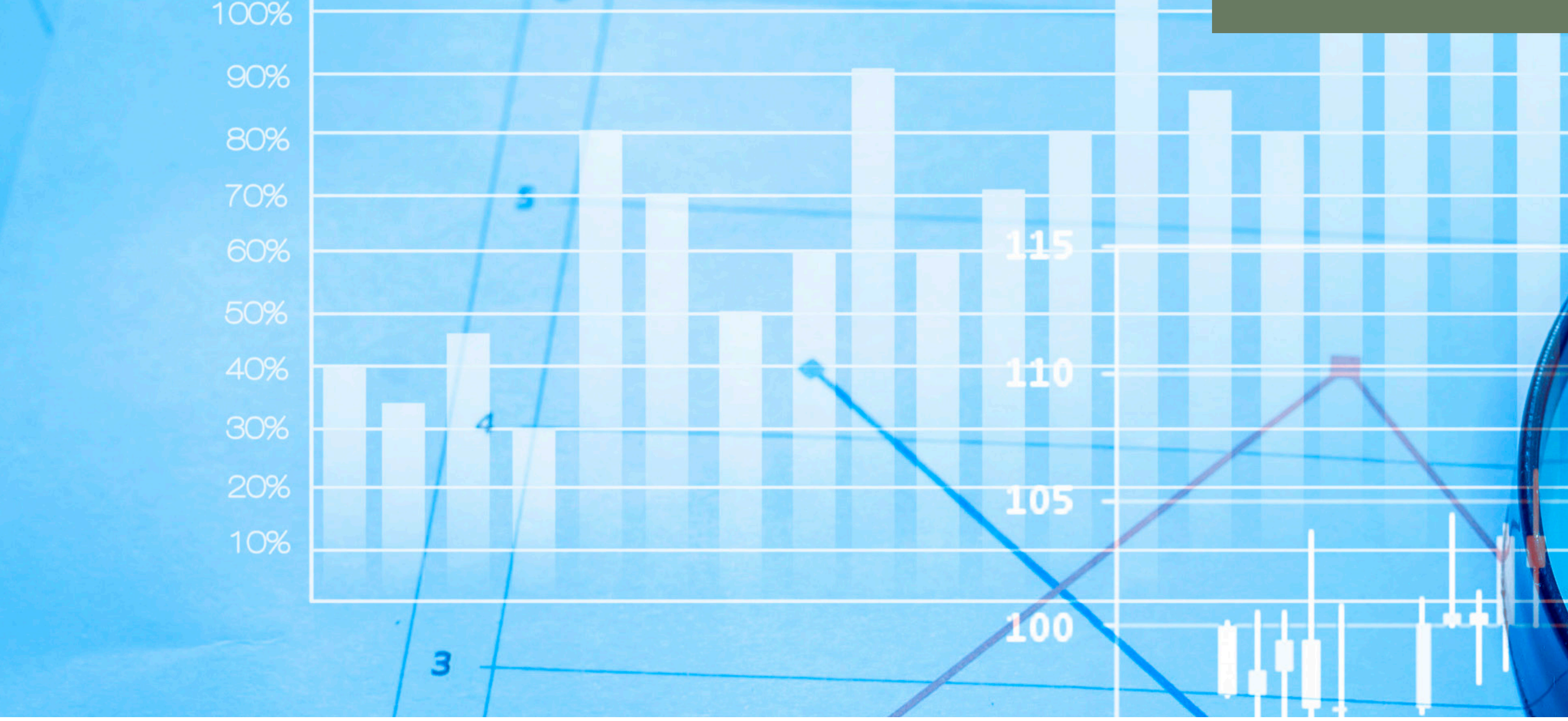
When a site had no workers, interviewers canvased the area for other sites, which generated a substantial number of additional interviews as reported in the results. An analog TLS sampling weight was developed for these individuals to allow for estimates using a combination of the randomly selected TLS sample and the convenience samples (or unselected sites) obtained when canvassing near selected sites. Additional details on sampling zones and the weights are presented in the **Appendix**.

LTS ANALYTIC STRATEGY

The outcome measures for the LTS sample aligned with those used in the TLS analysis, focusing on the PRIF definition criteria for the three periods of victimization: lifetime, past 2 years, and current job. The analysis involved calculating weighted means and proportions to adjust for the complex sampling design, with results reported as percentages in the **Findings section**.

Sampling weights for the network sample were derived through a statistical matching procedure, which was tested on the TLS sample to ensure the reliability of the approach. Given the lack of direct selection probabilities for the network sample, pseudo-probabilities were imputed using a beta regression model. The model incorporated key covariates, including the zone of the corresponding site, gender, disaster site worker status, and ratio of workers present to those interviewed. The imputed probabilities were then used to generate sampling weights for the network respondents.

As with the TLS sample, some of the imputed weights were extreme and were therefore trimmed to mitigate their influence on the estimates. The trimming procedure involved capping weights at five times the mean and one-fifth of the mean, following the guidance of Battaglia et al. (2004). This adjustment helped stabilize the estimates and reduce the potential impact of outliers. The final trimmed weights were used in the analysis to calculate weighted estimates for the network sample. Additional details on the statistical matching process and the imputation of pseudo-probabilities are provided in the **Appendix**.



FINDINGS

FULL STUDY SAMPLE

In total, 1,427 Houston construction workers completed the survey: 903 in the TLS sample and 524 in the LTS sample. **Exhibit 3** presents characteristics of the full sample. The average age was 37 years, and most survey respondents identified as being male (92%) and of Hispanic, Latino/a, or Spanish origin (88%). Only 15% of respondents were born in the United States, 33% were proficient or fluent in English, 60% had a high school degree or equivalency, and 51% were married.

Physical and cognitive disabilities were rare (1%). The most common types of employment were being employed full-time by a construction company (43%), being not currently employed or having another type of employment (25%), or working as a day laborer (20%). About 43% had worked in construction during the recovery and reconstruction efforts after a hurricane or other natural disaster.

Exhibit 3. Characteristics of the Full Sample (Unweighted)

	Full Sample (n = 1,427)	
	Unweighted Count	**Unweighted Proportion**
Mean age at survey	1,330	36.581
Race		
American Indian or Alaska Native	13	0.009
Asian	3	0.002
Black or African American	36	0.025
Native Hawaiian or Other Pacific Islander	3	0.002
White	641	0.449
No race selected; Hispanic	657	0.460
No race selected; non-Hispanic	14	0.010
No answer	60	0.042
Hispanic, Latino/a, or Spanish origin		
Yes	1,262	0.88
No	79	0.06
No answer	86	0.06
Gender		
Male	1,318	0.92
Female	104	0.07
Transgender, nonbinary, or gender not listed	5	0.01
Born in the United States		
Yes	214	0.15
No	1,148	0.80
No answer	65	0.05

	Full Sample (n = 1,427)	
	Unweighted Count	**Unweighted Proportion**
English proficiency		
No English	175	0.12
Minimal English (few words or simple sentences)	779	0.55
Proficient or fluent English	470	0.33
No answer	3	0.00
Highest education attained		
High school or GED with some college	493	0.35
High school or GED with no college	360	0.25
No high school diploma or GED but some high school	226	0.16
Less than high school	248	0.17
Don't know	27	0.02
Choose not to answer	66	0.05
Marital status		
Married	724	0.51
Not married	654	0.46
Don't know or no answer	49	0.03
Physical or cognitive disability		
No	1,409	0.99
Yes	18	0.01
Employment type		
Employed directly by a construction agency, full-time	614	0.43
Employed directly by a construction agency, part-time	67	0.05
Employed directly through a temporary job agency, full-time	83	0.06
Employed directly through a temporary job agency, part-time	18	0.01
Working as a day laborer	287	0.20
Not currently employed or other employment type	357	0.25
Involved in a union or other worker advocacy organization		
Yes	23	0.02
No	1402	0.98
Worked in construction during the recovery and reconstruction efforts after a hurricane or other natural disaster		
Yes	617	0.43
No	807	0.57

ANALYSIS SAMPLES

Exhibit 4 presents the characteristics of construction workers in Houston based on weighted findings of the TLS and LTS samples. A chi-square test was used for categorical variables to examine the associations between individual characteristics of the TLS and LTS samples. A nonsignificant p-value ($p > 0.05$) indicates that the characteristic is similarly distributed across the workers in the TLS sample and those in the LTS sample, whereas a significant p-value ($p < 0.05$) suggests a statistically significant difference in the distribution of the characteristic among the TLS and LTS samples. The samples were significantly different in nearly all respects. The only characteristics that were similar across samples were English proficiency, physical or cognitive disability, and union involvement. The mean age of survey respondents was older in the TLS sample (37 years) than in the LTS sample (34 years). Although a large majority identified as Hispanic , male, and born outside of the United States in both samples, they represented larger percentages of the TLS sample (86%, 96%, and 77%, respectively) than the LTS sample (70%, 78%, and 63%, respectively). Most respondents in both samples spoke minimal (52%–55%) or no (10%–12%) English. Members of the TLS sample attained higher levels of education; about 63% of the TLS sample had a high school degree or equivalent, compared with 56% in the LTS sample. Only 1% of both samples reported having a physical or cognitive disability. The employment situations of respondents varied significantly by sample. Although over half of both samples reported working full-time (49% working full-time for a construction company and 4%–7% working full-time for a temporary job agency); only 8% of the TLS sample reported working as day laborers, compared with 21% of the LTS sample; and 33% of the TLS sample reported not working for a construction company, temporary agency, or as a day laborer, compared with only 10% of the LTS sample. More respondents in the LTS sample (50%) than in the TLS sample (39%) indicated that they had worked construction during the recovery or reconstruction efforts after a hurricane or other natural disaster.

Exhibit 4. Characteristics of Construction Workers in Houston (TLS and LTS Samples, Weighted)

	TLS Sample (n=903)			LTS Sample (n=262)		
	Unweighted Count	Unweighted Mean	Weighted Mean (SE)	Unweighted Count	Unweighted Mean	Weighted Mean (SE)
Mean age at survey*	849	36.323	36.603 (0.665)	225	32.853	33.553 (0.655)
Race*						
American Indian or Alaska Native	4	0.004	0.003 (0.002)	6	0.023	0.028 (0.012)
Asian	1	0.001	0.0007 (0.0007)	2	0.008	0.021 (0.018)
Black or African American	21	0.023	0.039 (0.013)	6	0.023	0.027 (0.013)
Native Hawaiian or Other Pacific Islander	2	0.002	0.001 (0.0008)	1	0.004	0.002 (0.002)
White	376	0.416	0.434 (0.023)	124	0.473	0.454 (0.037)
No race selected; Hispanic	467	0.517	0.484 (0.022)	89	0.340	0.324 (0.033)
No race selected; non-Hispanic	7	0.008	0.007 (0.003)	4	0.015	0.023 (0.012)
No answer	25	0.028	0.031 (0.008)	30	0.115	0.121 (0.024)

	TLS Sample (n=903)			LTS Sample (n=262)		
	Unweighted Count	Unweighted Mean	Weighted Mean (SE)	Unweighted Count	Unweighted Mean	Weighted Mean (SE)
Hispanic, Latino/a, or Spanish origin*						
Yes	814	0.90	0.863 (0.021)	200	0.763	0.700 (0.037)
No	53	0.06	0.088 (0.021)	20	0.076	0.141 (0.035)
No answer	36	0.04	0.049 (0.010)	42	0.160	0.159 (0.026)
Gender*,†						
Male	866	0.96	0.960 (0.009)	197	0.752	0.780 (0.029)
Female	37	0.04	0.040 (0.009)	65	0.248	0.220 (0.029)
Born in the United States*						
Yes	150	0.17	0.207 (0.022)	48	0.183	0.233 (0.035)
No	733	0.81	0.769 (0.023)	177	0.676	0.629 (0.036)
No answer	20	0.02	0.025 (0.006)	37	0.141	0.138 (0.026)
English proficiency						
No English	92	0.10	0.097 (0.014)	30	0.115	0.103 (0.020)
Minimal English (few words or simple sentences)	494	0.55	0.505 (0.026)	136	0.519	0.503 (0.035)
Proficient or fluent English	314	0.35	0.392 (0.029)	96	0.366	0.394 (0.035)
No answer	3	0.00	0.006 (0.004)	0	-	-
Highest education attained*						
High school or GED with some college	360	0.40	0.411 (0.024)	65	0.249	0.368 (0.019)
High school or GED with no college	209	0.23	0.219 (0.018)	89	0.341	0.256 (0.017)
No high school diploma or GED but some high school	142	0.16	0.160 (0.015)	42	0.161	0.157 (0.014)
Less than high school	160	0.18	0.174 (0.017)	15	0.058	0.155 (0.015)
Don't know	7	0.01	0.009 (0.005)	17	0.065	0.020 (0.006)
Choose not to answer	22	0.02	0.026 (0.007)	33	0.126	0.044 (0.007)

	TLS Sample (n=903)			LTS Sample (n=262)		
	Unweighted Count	Unweighted Mean	Weighted Mean (SE)	Unweighted Count	Unweighted Mean	Weighted Mean (SE)
Marital status*						
Married	485	0.54	0.549 (0.022)	121	0.462	0.502 (0.037)
Not married	397	0.44	0.427 (0.021)	117	0.447	0.421 (0.037)
Don't know or no answer	21	0.02	0.024 (0.005)	24	0.092	0.077 (0.019)
Physical or cognitive disability						
No	891	0.99	0.989 (0.004)	259	0.989	0.982 (0.012)
Yes	12	0.01	0.011 (0.004)	3	0.012	0.018 (0.012)
Employment type*						
Employed directly by a construction agency, full-time	438	0.49	0.492 (0.023)	123	0.470	0.485 (0.033)
Employed directly by a construction agency, part-time	20	0.02	0.023 (0.008)	34	0.130	0.127 (0.025)
Employed directly through a temporary job agency, full-time	66	0.07	0.068 (0.011)	12	0.046	0.041 (0.016)
Employed directly through a temporary job agency, part-time	9	0.01	0.014 (0.007)	7	0.046	0.020 (0.009)
Working as a day laborer	74	0.08	0.076 (0.012)	56	0.214	0.214 (0.029)
Not currently employed or other employment type	295	0.33	0.327 (0.021)	30	0.115	0.102 (0.023)
Involved in a union or other worker advocacy organization						
Yes	12	0.01	0.021 (0.008)	5	0.019	0.046 (0.021)
No	889	0.98	0.977 (0.008)	257	0.981	0.954 (0.021)
Worked in construction during the recovery and reconstruction efforts after a hurricane or other natural disaster*						
Yes	356	0.40	0.394 (0.026)	130	0.496	0.505 (0.038)
No	545	0.60	0.606 (0.026)	132	0.504	0.495 (0.038)

* The finding was significant at the $p < 0.05$ level.

† Other gender options were available on the survey but received zero affirmative responses, including (1) transgender, (2) nonbinary, and (3) my gender is not listed here.

RESEARCH QUESTION 1: HOW DO THE NUMBER AND CHARACTERISTICS OF CONSTRUCTION WORKERS WHO SELF-REPORTED EXPLOITATION AND TRAFFICKING EXPERIENCES COMPARE BY PREVALENCE ESTIMATION STRATEGY?

As shown in **Exhibit 5**, the prevalence estimates are higher among the LTS sample members than among TLS sample members at all three timeframes. Estimates from the TLS sample indicate that 22% of construction workers experienced labor trafficking at some point during their lifetime, 13% experienced labor trafficking in the past 2 years, and 4% experienced labor trafficking in their current job.[3] Estimates from the LTS sample indicate that 36% of construction workers experienced labor trafficking at some point during their lifetime, 30% experienced labor trafficking in the past 2 years, and 18% experienced labor trafficking in their current job. **These results are presented simply to underscore that the chosen estimation strategy may impact the findings.** Because of the failure of referral chains to adequately develop in the LTS sample and the concerns about potentially misleading findings, we use only the TLS sample for the remaining analyses.

Exhibit 6 presents a profile of individuals who experienced labor trafficking across the three time points. The characteristics of individuals who experienced lifetime labor trafficking mostly reflected their composition of the survey sample. For example, nearly all individuals who experienced labor trafficking identified as male. Over 80% identified as Hispanic, 74% were not born in the United States, and over 60% spoke no or minimal English. One notable difference was among individuals who worked in natural disaster recovery and reconstruction—although they represented only 39% of the sample, they represented 57% of individuals who experienced labor trafficking in their lifetime, 54% in the past 2 years, and 50% at their current job.

Exhibit 5. Labor Trafficking Prevalence Estimates, by Sample and Timeframe

	Lifetime		Past 2 Years		Current Job	
	n	Point Estimate (CI)	n	Point Estimate (CI)	n	Point Estimate (CI)
TLS (n = 903)	220	22.3% (18.85, 25.84)	147	13.23% (10.62, 15.84)	42	4.18%(2.65, 5.72)
LTS (n = 262)	94	35.5% (0.288, 0.421)	78	29.9% (0.238, 0.361)	40	17.6% (0.121, 0.231)

[3] Because individuals have been at their current job for different lengths of time (e.g., 1 week, 10 years), the current job measure captured a few individuals whose exploitation occurred more than 2 years in the past (i.e., they were not included in the past 2 years measure).

Exhibit 6. Characteristics of Construction Workers Who Experienced Labor Trafficking, by Timeframe

	TLS Sample (n = 903)			
	Total Sample	Lifetime	Flow (past 2 years)	Stock (current)
	Weighted TLS Mean (SE)	Point Estimate (CI)	Point Estimate (CI)	Point Estimate (CI)
Mean age at survey	36.603 (0.665)	35.581 (33.709, 37.453)	34.734 (32.350, 37.118)	35.425 (31.854, 38.995)
Race				
American Indian or Alaska Native	0.003 (0.002)	0.002 (0.000, 0.006)	-	-
Asian	0.0007 (0.0007)	-	-	-
Black or African American	0.039 (0.013)	0.048 (0.000, 0.101)	0.039 (0.000, 0.081)	0.059 (0.000, 0.171)
Native Hawaiian or Other Pacific Islander	0.001 (0.0008)	0.002 (0.000, 0.005)	0.003 (0.000, 0.008)	-
White	0.434 (0.023)	0.422 (0.333, 0.511)	0.388 (0.285, 0.491)	0.580 (0.400, 0.76)
No race selected; Hispanic	0.484 (0.022)	0.488 (0.400, 0.577)	0.534 (0.431, 0.638)	0.276 (0.137, 0.415)
No race selected; non-Hispanic	0.007 (0.003)	0.004 (0.000, 0.010)	0.006 (0.000, 0.018)	-
No answer	0.031 (0.008)	0.035 (0.000, 0.010)	0.030 (0.000, 0.072)	0.084 (0.000, 0.202)
Hispanic, Latino/a, or Spanish origin				
Yes	0.863 (0.021)	0.832 (0.750, 0.912)	0.895 (0.820, 0.969)	0.706 (0.516, 0.895)
No	0.088 (0.021)	0.111 (0.037, 0.184)	0.059 (0.010, 0.107)	0.151 (0.000, 0.314)
No answer	0.049 (0.010)	0.058 (0.019, 0.097)	0.047 (0.000, 0.095)	0.144 (0.000, 0.293)
Gender[*,†]				
Male	0.960 (0.009)	0.980 (0.963, 0.997)	0.984 (0.967, 1.000)	0.976 (0.930, 1.000)
Female	0.040 (0.009)	0.020 (0.003, 0.037)	0.016 (0.000, 0.033)	0.024 (0.000, 0.070)
Born in the United States				
Yes	0.207 (0.022)	0.227 (0.142, 0.313)	0.208 (0.117, 0.300)	0.252 (0.089, 0.416)
No	0.769 (0.023)	0.744 (0.657, 0.831)	0.779 (0.684, 0.874)	0.717 (0.540, 0.895)
No answer	0.025 (0.006)	0.029 (0.004, 0.053)	0.012 (0.000, 0.031)	0.030 (0.000, 0.086)
English proficiency				
No English	0.097 (0.014)	0.051 (0.018, 0.085)	0.073 (0.022, 0.124)	0.128 (0.000, 0.263)
Minimal English (few words or simple sentences)	0.505 (0.026)	0.562 (0.470, 0.654)	0.577 (0.479, 0.675)	0.529 (0.364, 0.694)
Proficient or fluent English	0.392 (0.029)	0.386 (0.294, 0.478)	0.349 (0.253, 0.445)	0.343 (0.184, 0.502)

	TLS Sample (n = 903)			
	Total Sample	Lifetime	Flow (past 2 years)	Stock (current)
	Weighted TLS Mean (SE)	Point Estimate (CI)	Point Estimate (CI)	Point Estimate (CI)
Highest education attained				
Yes, high school or GED with some college	0.411 (0.024)	0.424 (0.329, 0.519)	0.384 (0.286, 0.483)	0.424 (0.251, 0.598)
Yes, HS or GED, No College	0.219 (0.018)	0.259 (0.188, 0.329)	0.313 (0.220, 0.407)	0.270 (0.114, 0.426)
No high school diploma or GED but some high school	0.160 (0.015)	0.154 (0.089, 0.220)	0.116 (0.061, 0.170)	0.046 (0.001, 0.091)
Less than high school	0.174 (0.017)	0.130 (0.076, 0.182)	0.175 (0.096, 0.254)	0.196 (0.059, 0.332)
Don't know	0.009 (0.005)	0.007 (0.000, 0.020)	–	–
Choose not to answer	0.026 (0.007)	0.026 (0.003, 0.050)	0.011 (0.000, 0.030)	0.064 (0.000, 0.140)
Marital status				
Married	0.549 (0.022)	0.500 (0.413, 0.586)	0.435 (0.339, 0.531)	0.480 (0.309, 0.651)
Not married	0.427 (0.021)	0.457 (0.369, 0.544)	0.539 (0.441, 0.637)	0.460 (0.287, 0.633)
Don't know or no answer	0.024 (0.005)	0.043 (0.011, 0.076)	0.026 (0.000, 0.064)	0.060 (0.000, 0.170)
Physical or cognitive disability				
No	0.989 (0.004)	0.984 (0.971, 0.997)	0.980 (0.963, 0.998)	0.990 (0.972, 1.000)
Yes	0.011 (0.004)	0.016 (0.003, 0.029)	0.020 (0.002, 0.037)	0.010 (0.000, 0.028)
Employment type				
Employed directly by a construction agency, full-time	0.492 (0.023)	0.425 (0.332, 0.518)	0.404 (0.305, 0.502)	0.573 (0.385, 0.760)
Employed directly by a construction agency, part-time	0.023 (0.008)	0.043 (0.002, 0.084)	0.073 (0.006, 0.139)	0.013 (0.000, 0.039)
Employed directly through a temporary job agency, full-time	0.068 (0.011)	0.112 (0.049, 0.175)	0.093 (0.026, 0.159)	0.033 (0.000, 0.084)
Employed directly through a temporary job agency, part-time	0.014 (0.007)	0.007 (0.000, 0.016)	0.004 (0.000, 0.013)	–
Working as a day laborer	0.076 (0.012)	0.099 (0.052, 0.145)	0.122 (0.057, 0.187)	0.042 (0.000, 0.088)
Not currently employed or other employment type	0.327 (0.021)	0.315 (0.231, 0.399)	0.304 (0.220, 0.388)	0.339 (0.156, 0.522)
Worked in construction during the recovery and reconstruction efforts after a hurricane or other natural disaster*				
Yes	0.394 (0.026)	0.571 (0.479, 0.664)	0.542 (0.442, 0.642)	0.498 (0.308, 0.688)
No	0.606 (0.026)	0.429 (0.336, 0.521)	0.458 (0.358, 0.558)	0.502 (0.312, 0.692)

* The finding was significant at the $p < 0.05$ level.

† Other gender options were available on the survey but received zero affirmative responses, including (1) transgender, (2) nonbinary, and (3) my gender is not listed here.

The remaining results in this report are based on members of this TLS analysis sample, which does not include individuals who were recruited from areas where day laborers congregate or were referred by a peer to participate in the study.

RESEARCH QUESTION 2: WHAT IS THE NATURE AND TYPE OF EXPLOITATION EXPERIENCED BY CONSTRUCTION WORKERS?

To better understand the nature of exploitation that construction workers experience, we present responses to the individual trafficking indicators in **Exhibits 7–13.** This section is organized by category of trafficking indicator.

Recruitment

Over one-quarter of respondents indicated that they had experienced deception about their working and living conditions during recruitment, such as deceptions about work conditions, housing or living arrangements, location of the job, or identity of the employer. Nearly 20% had to pay a recruitment or broker fee to help get a job. Less frequently, study participants reported being deceived about the nature of the job, such as work responsibilities, pay or compensation, and hours of work (13%) or feeling obligated or pressured to take a job against their will (5%).

Exhibit 7. Nature and Type of Exploitation Experienced: Recruitment

Exploitation During Recruitment	Weighted Proportion (%)
Deceptive recruitment: Working and living conditions	30.10%
Paid recruitment fees or paid transportation recruitment fees	18.39%
Deceptive recruitment: Nature of the job	12.99%
Coercive recruitment	5.00%

Employment Practices and Penalties

The most common form of exploitative employment practice involved working without a formal contract (38%). More than 1 in 10 respondents had unfairly accumulated a high or increasing debt to their employer (17%); had their pay or benefits deducted or withheld without cause (13%); or were made to perform additional or specialized services that went beyond their agreement without appropriate pay (13%). Less frequently, participants had their pay or benefits withheld to prevent them from leaving or quitting (8%) or borrowed money or took a loan as a condition of getting a job (3%).

Exhibit 8. Nature and Type of Exploitation Experienced: Employment Practices and Penalties

Exploitative Employment Practices and Penalties	Weighted Proportion (%)
Absence of a formal contract	37.79%
High or increasing debt related to an employer	16.65%
Pay, benefits, or compensation deducted or withheld for no reason	13.15%
Made to perform additional services or responsibilities	12.93%
Had pay or benefits withheld to prevent you from leaving or quitting	8.24%
Borrowed money as a condition of employment	3.24%

Personal Life and Property

Exploitation related to control over one's personal life and property were not commonly experienced by study participants. Over 3% indicated that their employer had attempted to control their personal life outside of work, such as threatening to reveal something personal or embarrassing about them, preventing them from participating in religious activities, and threatening to isolate them from their friends or family. Less than 2% had their phone or another communication device confiscated by their employer.

Exhibit 9. Nature and Type of Exploitation Experienced: Personal Life and Property

Personal Life and Property	Weighted Proportion (%)
Another individual has control over a meaningful part of your personal life	3.73%
Mobile phone or communication device confiscated	1.88%

Degrading Conditions

Nearly one in five respondents were required to work longer than normal hours, unusually long days, or outside of normal work hours without being properly compensated for overtime. Less frequently, study participants indicated that they were made to work without proper health and safety equipment (14%), to engage in illegal activities for their employer (3%), or to live in degrading (e.g., unclean, overcrowded, dangerous, hazardous to their health) conditions (1%).

Exhibit 10. Nature and Type of Exploitation Experienced: Degrading Conditions

Degrading Conditions	Weighted Proportion (%)
Made to be available day and night without adequate compensation outside contract	17.42%
Made to complete hazardous services without proper protective gear	14.12%
Made to engage in illicit activities	2.96%
Made to live in degrading conditions	1.47%

Restrictions to Freedom of Movement or Communication

Restrictions to workers' freedoms were relatively rare. The most common example involved being always watched or monitored at work (14%). Less frequently, workers indicated that they had no freedom of movement or communication (e.g., not able to visit or communicate with someone) (3%), had limited freedom (e.g., communication or movement was limited or supervised) (2%), or were constantly surveilled in their personal space (1%). Fewer than 1% of participants had their identity documents confiscated.

Exhibit 11. Nature and Type of Exploitation Experienced: Restrictions to Freedom of Movement or Communication

Restrictions to Freedom of Movement or Communication	Weighted Proportion (%)
Constant surveillance of place of work	14.29%
No freedom of movement and communication	3.18%
Limited freedom of movement and communication	2.10%
Constant surveillance of personal spaces by employer, recruiter, or other individuals	0.77%
Confiscation or loss of access to identity papers or travel documents	0.38%

Debt or Dependency

Debt to an employer—such as being charged fees for goods or services purchased from an employer or being charged excessive interest on a loan to repay an employer—was rare among the study population. Fewer than 2% of respondents indicated that an employer had ever imposed a debt on them without their consent.

Exhibit 12. Nature and Type of Exploitation Experienced: Debt or Dependency

Debt or Dependency	Weighted Proportion (%)
Had a debt imposed on you without your consent	1.53%

Violence or Threats of Violence

The most common form of violence reported by study participants involved emotional or psychological abuse (8%). Fewer than 4% of respondents indicated that they had experienced threats to harm their reputation (3%), threats of denunciation to authorities (2%), physical violence inflicted in front them (3%), or threats of physical violence (3%). Even less frequently, respondents indicated having experienced physical violence (0.54%) or having received threats of sexual violence (0.12%). No respondents indicated having experienced sexual violence.

Exhibit 13. Nature and Type of Exploitation Experienced: Violence or Threats of Violence

Violence or Threats of Violence	Weighted Proportion (%)
Emotional or psychological abuse against you or someone you care deeply about	8.47%
Threat of harm to your personal or professional reputation	2.67%
Threat of denunciation to authorities against you or someone you care deeply about	1.72%
Physical violence inflicted in front of you on other individuals	2.52%
Threatened physical violence against you or someone you care about	2.72%
Physical violence against you or someone you care about	0.54%
Threatened sexual violence against you or someone you care about	0.12%
Sexual violence against you or someone you care deeply about	0.00%

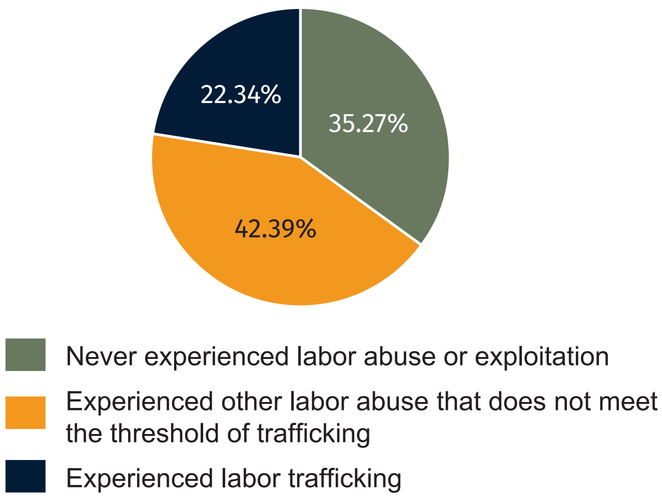
SUMMARY

Construction workers in Houston experienced a broad range of exploitation at the hands of their employers. The most common forms of exploitation included working without a contract (38%), being deceived during recruitment about working and living conditions (30%), paying recruitment fees (18%), and being made to work long and unusual hours without adequate compensation (17%). Although less serious forms of exploitation appear to be the most common, nontrivial percentages of workers were subjected to more serious forms of exploitation, such as having their pay withheld (13%), being deceived during recruitment about the work they would be doing (13%), and being subjected to emotional or psychological abuse (8%). Although the focus of this study was on labor trafficking, these forms of exploitation should not be ignored or overlooked. It is important to understand the frequency of other types of labor exploitation to increase workplace safety and justice for all workers. Measuring and responding to a wider range of experiences with exploitation in the workplace may also capture environments in which labor trafficking is more likely to occur (Zhang et al., 2014).

RESEARCH QUESTION 3: WHAT ARE THE POTENTIAL RISK AND PROTECTIVE FACTORS ASSOCIATED WITH TRAFFICKING VICTIMIZATION?

Based on their survey responses, study participants were assigned to one of three categories: (1) never experienced labor abuse or exploitation, (2) experienced other labor abuse that did not meet the threshold of labor trafficking, or (3) experienced labor trafficking. Nearly two-thirds of respondents reported being abused or exploited while working in the industry: 22% experienced labor trafficking and an additional 42% experienced other abuse or exploitation that did not rise to the level of trafficking (**Exhibit 14**).[4] Profiles of the individuals who comprise each category were created to explore whether individual characteristics or employment experiences differentiate construction workers who report labor trafficking and other labor abuses from those who do not.

Exhibit 14. Lifetime Labor Trafficking and Other Labor Abuse



[4] Percentages reported are weighted to represent the population. Percentages reported are weighted to represent the population.

Individual Characteristics

To help identify characteristics that may put someone at greater or lesser risk for labor trafficking or other labor abuse, profiles of the individuals in each category of abusive experiences were created (**Exhibit 15**). A chi-square test was used to examine the associations between individual characteristics and the victimization groups. A nonsignificant p-value ($p > 0.05$) indicates that the characteristic is similarly distributed across the victimization groups, whereas a significant p-value ($p < 0.05$) suggests a statistically significant difference in the distribution of the characteristic among the victimization groups. Although small differences across individual characteristics emerged, none were statistically significant. A few interesting patterns that warrant additional research are noted. For example, individuals who identify as being female and of Hispanic, Latino/a, or Spanish origin were less likely, albeit not significantly less likely, to experience labor trafficking. Neither education nor marriage serve as protective factors for labor trafficking or other labor abuse.

The results for English proficiency present an interesting, but not statistically significant, pattern. Although larger percentages of individuals who can speak a few words or simple sentences in English were observed among those who experienced labor trafficking, individuals who speak no English were over-represented among those who had experienced other labor abuse but under-represented among those who experienced labor trafficking. Although few respondents ($n = 12$) identified as having a physical or cognitive disability, they were over-represented among those who experienced labor trafficking but not among those who experienced other labor abuse (relationship not statistically significant).

Exhibit 15. Individual-Level Risk and Protective Factors, by Labor Trafficking and Other Labor Abuse Experiences (Weighted Proportions)

	Total TLS Sample	Did Not Experience Labor Abuse	Experienced Other Labor Abuse Not Meeting Trafficking Threshold	Experienced Labor Trafficking
Hispanic, Latino/a, or Spanish origin				
Yes	86.3%	89.34%	85.61%	83.15%
No	8.8%	6.74%	9.23%	11.07%
No answer	4.9%	3.92%	5.16%	5.78%
Gender†				
Male	96.0%	95.29%	95.61%	98.01%
Female	4.0%	4.71%	4.39%	1.99%
Born in the United States				
Yes	20.7%	20.24%	19.92%	22.72%
No	76.9%	78.14%	77.14%	74.39%
No answer	2.5%	1.62%	2.94%	2.89%
English proficiency				
No English	9.7%	11.37%	10.70%	5.14%
Minimal English (few words or simple sentences)	50.5%	47.19%	50.23%	56.24%
Proficient or fluent English	39.2%	40.90%	38.04%	38.61%
No answer	0.6%	0.53%	1.03%	-
Martial status				
Married	54.9%	59.09%	54.05%	49.97%
Not Married	42.7%	38.54%	44.63%	45.67%
Don't know or no answer	2.4%	2.37%	1.32%	4.36%
Physical or cognitive disability				
No	98.9%	99.50%	98.72%	98.44%
Yes	1.1%	0.50%	1.28%	1.56%
Highest education completed				
High school or GED with at least some college	41.1%	40.72%	40.81%	42.42%
High school or GED with no college	21.9%	19.37%	21.94%	25.88%
No high school diploma or GED but some high school	16.0%	16.39%	16.00%	15.44%
Less than high school	17.4%	20.78%	17.04%	12.95%
Don't know	0.9%	1.25%	0.79%	0.68%
Choose not to answer	2.6%	1.49%	3.41%	2.63%

†Other gender options were available on the survey but received zero affirmative responses, including (1) transgender, (2) nonbinary, and (3) my gender is not listed here.

Note: Nothing in this exhibit was found to be significant at the $p < 0.05$ level.

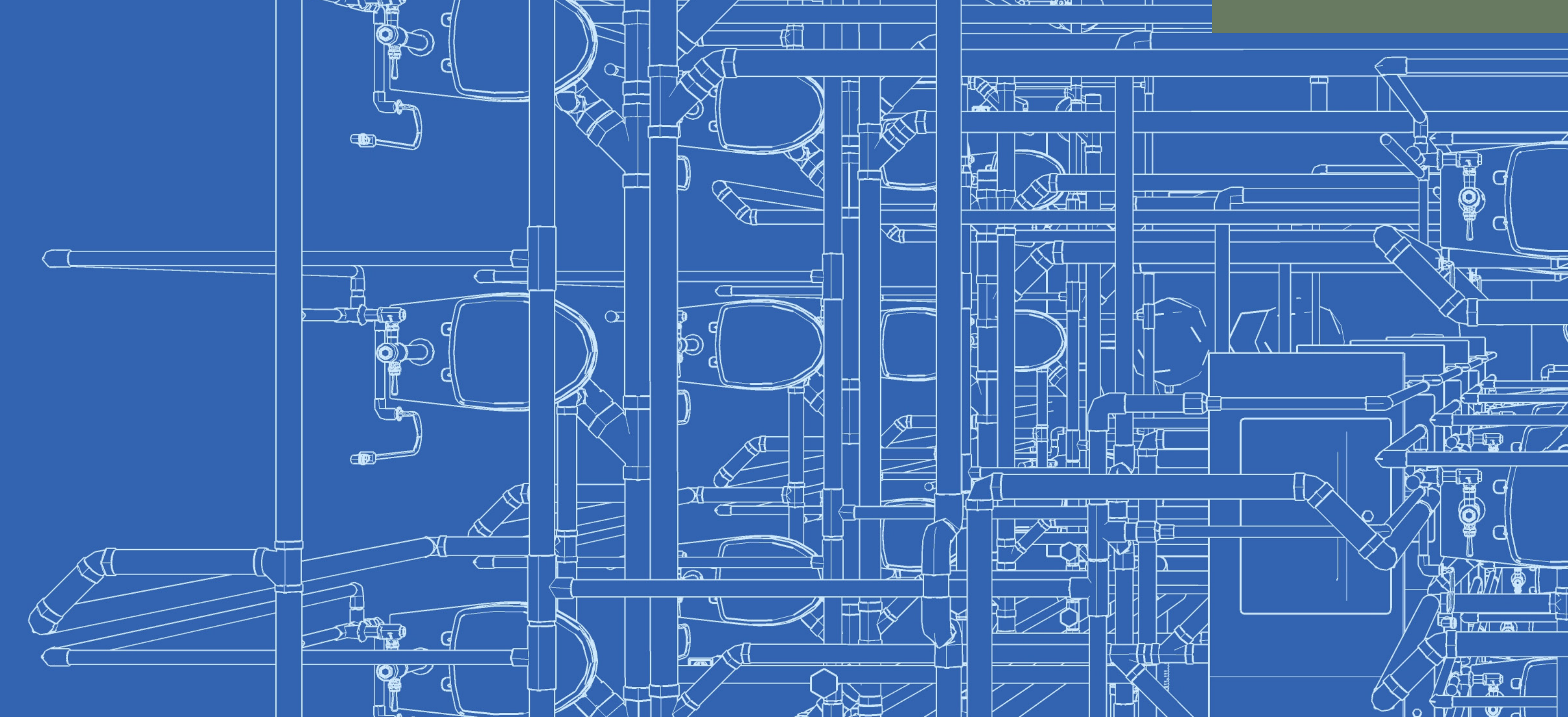
Employment Experiences

To help identify work experiences that may put someone at greater risk for labor trafficking or other labor abuse in construction, profiles of the employment conditions of individuals who represent each category of abusive experiences were created, and significance tests were run (**Exhibit 16**). Similar to individual characteristics, most employment experiences were not significantly associated with experiences of labor trafficking or other labor abuse. Yet, some patterns, although not significant, followed expectations. For example, individuals who worked full-time for a construction company were over-represented among individuals who did not experience labor abuse and under-represented among those who experienced labor trafficking or other labor abuse; however, these differences were not significant. Similarly, although larger percentages of individuals working as day laborers were observed among those who experienced labor trafficking and other labor abuse, the result is not statistically significant. The largest, and only statistically significant, differentiator between construction workers who have not experienced any workplace exploitation and those who have experienced labor trafficking or other exploitation involves having worked during the clean-up and reconstruction efforts after a natural disaster.

Exhibit 16. Employment-Level Risk and Protective Factors, by Labor Trafficking and Other Labor Abuse Experiences (Weighted Proportions)

	Total Sample	Did Not Experience Labor Abuse	Experienced Other Labor Abuse Not Meeting Trafficking Threshold	Experienced Labor Trafficking
Employment type				
Employed directly by a construction agency, full-time	49.2%	55.85%	47.12%	42.49%
Employed directly by a construction agency, part-time	2.3%	1.91%	1.61%	4.30%
Employed directly through a temporary job agency, full-time	6.8%	5.33%	5.76%	11.20%
Employed directly through a temporary job agency, part-time	1.4%	1.38%	1.86%	0.69%
Working as a day laborer	7.6%	4.49%	8.95%	9.85%
Not currently employed or other employment type	32.7%	31.04%	34.70%	31.46%
Involved in a union or other worker advocacy organization				
Yes	2.1%	0.63%	3.30%	2.25%
No	97.7%	99.37%	96.30%	97.75%
Worked in construction during the recovery and reconstruction efforts after a hurricane or other natural disaster*				
Yes	39.4%	24.15%	42.85%	57.12%
No	60.6%	75.85%	57.15%	42.88%

*Indicates that the finding was significant at the $p < 0.05$ level

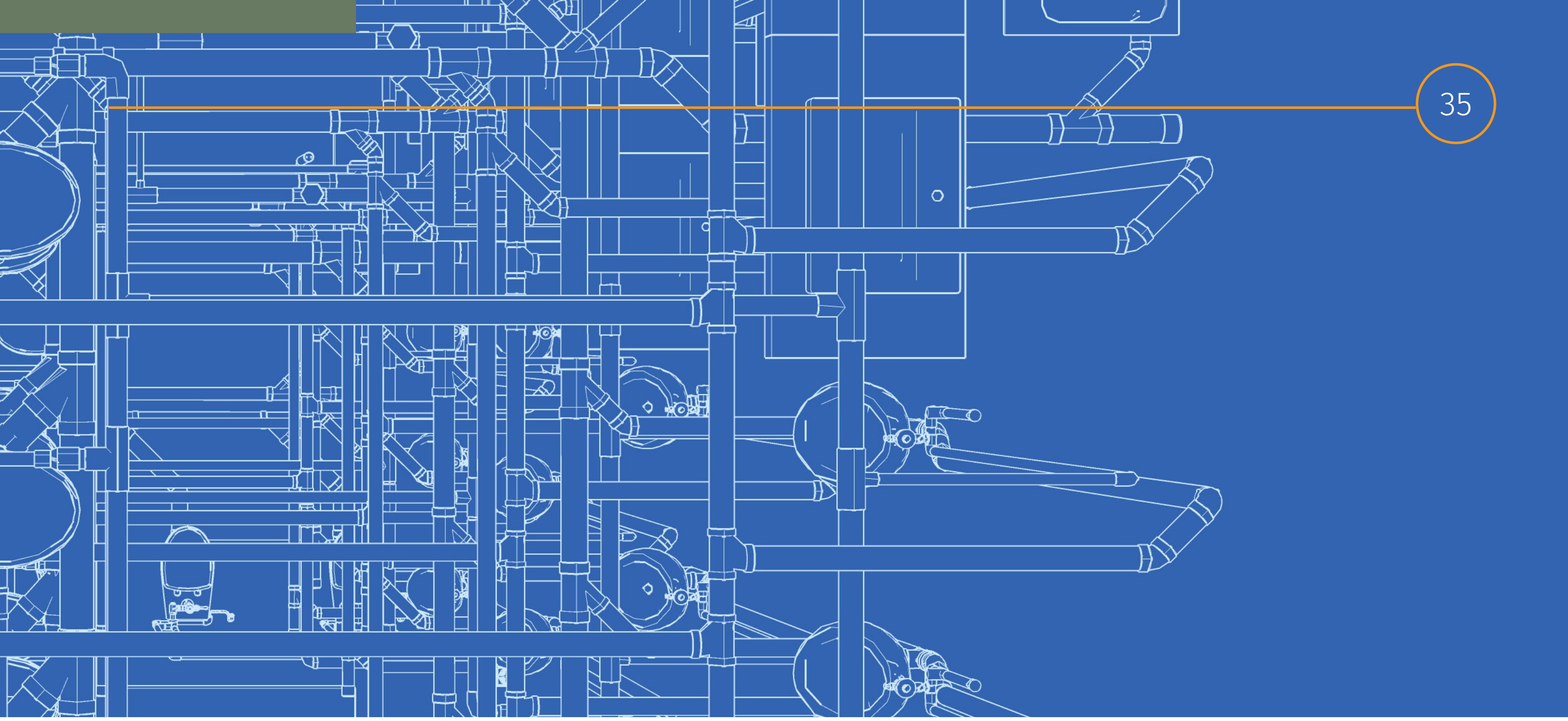


CONCLUSIONS AND IMPLICATIONS

SUMMARY OF FINDINGS AND KEY TAKEAWAYS

Labor trafficking and other labor abuse in the construction industry is common. About two-thirds of Houston construction workers experienced at least one form of exploitative labor practice. Nearly one in four Houston construction workers (22%) experienced labor trafficking in their lifetime; 13% experienced labor trafficking in the past 2 years; and 4% experienced labor trafficking in their current job. Other forms of labor abuses and exploitation that do not meet the threshold of labor trafficking were experienced by over 40% of construction workers. These findings resonate with the limited prior research with this population. In a study using RDS to recruit undocumented migrant workers in San Diego, Zhang et al. (2014) found that 65% of construction workers experienced at least one form of labor exploitation, with 35% experiencing labor trafficking in their lifetime. Although Zhang et al.'s estimate for lifetime labor trafficking prevalence among construction workers was higher than that of this study, Zhang et al. focused on a narrower population (i.e., undocumented migrant workers) that may be more susceptible than the general population to labor exploitation. The differences may also be the result of using different sampling strategies (TLS vs. RDS), which may impact the population that is reachable.

The types of exploitation most frequently experienced by construction workers include working without a contract, deception about working and living conditions, long or unusual hours without adequate compensation, and paying recruitment fees to get a job. However, nontrivial percentages of construction workers were subjected to more serious forms of exploitation, including having their pay withheld, deception about the work they would be doing, and subjection to emotional or psychological abuse. These findings resonate with the limited prior research on labor abuse in the construction industry. For example, Juravich, Ablavsky, and Williams (2015) found that wage theft is rampant in this sector, and labor trafficking situations that



involved construction workers and were reported to the National Human Trafficking Hotline were characterized as involving wage reduction and withholding and verbal abuse, harassment, and denial of necessities (Polaris, 2017). Although not specific to the construction industry, federally prosecuted forced-labor cases frequently involved fraudulent job offers and misrepresentation of the work, withholding pay, and verbal or emotional abuse (Lane et al., 2022).

Although individual characteristics and employment experiences were assessed as potential risk and protective factors, only one significant difference emerged.

Work during the recovery and reconstruction efforts after a natural disaster was the largest differentiator between individuals who experienced labor trafficking or other labor abuse and those who did not: individuals who worked in construction post-disaster exhibited higher rates of labor trafficking and other labor abuse. This finding is consistent with growing anecdotal evidence that workers engaged in post-disaster construction may encounter fatal or injurious working conditions, unsafe living conditions, stolen wages, assault, and labor trafficking (Stillman, 2021). With the limited extant research focusing on risk and protective factors for individuals experiencing labor trafficking or other labor abuse in construction, additional work is needed to substantiate the lack of significant findings regarding individual characteristics and employment experiences reported here.

For more detailed information about study findings related to labor trafficking that occurs post-disaster, see Labor Trafficking in Construction During the Recovery and Reconstruction from a Natural Disaster.

REFLECTION SESSIONS

Findings from the study were shared with practitioners (n = 5) and impacted communities (i.e., construction workers, n = 7) in separate reflection sessions. The sessions were held in person in Houston to solicit feedback on what we learned, including whether the findings resonated or differed from their experiences, the most important findings to share with different communities, and potential policy or practice implications of the information. Input included personal and professional anecdotes that provided context for the group discussions of the study findings, requests for clarification, and suggestions for policy and practice. Suggestions that were within the scope of the project and were supported by study data were incorporated throughout the report.

IMPLICATIONS FOR FUTURE HUMAN TRAFFICKING PREVALENCE ESTIMATION STUDIES

Of critical importance, we confirmed that data collection and prevalence estimation strategies matter. Although both TLS and LTS were promising approaches for identifying and recruiting construction workers, only TLS proved to be effective in reaching the population. The approaches also seemed to identify different populations within the construction industry (i.e., the characteristics of members of the TLS and LTS samples were significantly different in nearly all respects), which suggests that multiple methods may be needed to accurately capture the experiences of the entire population of construction workers. Alternatively, prevalence studies may need to focus on narrower populations (e.g., day laborers who work in construction). All prevalence estimation research should clearly highlight challenges that occurred during data collection that may impact the validity of the findings and should exercise caution in reporting potentially misleading estimates. Additional lessons were learned about using each of the sampling and recruitment strategies.

Lessons Learned About TLS

Publicly available lists of permitted construction sites were initially appealing to serve as the foundation for the TLS sample; however, they were not effective in the current study. Workers were typically not present during the day and time slots the field team was assigned to visit. We speculate that it is because a permit covers a much longer time than is needed to complete the construction project. For example, a permit may be pulled for 6 months, when the project may be completed in 1 week. Moreover, although permits are required for construction, they are not always pulled. To ensure the inclusion of nonpermitted construction, the field team also visually canvassed blocks surrounding the selected sites to identify construction sites for inclusion in the sample. The field team had more success recruiting construction workers at the nonpermitted sites. In lieu of a TLS sample, it may be more efficient to randomly sample geographic areas (e.g., Census tracts, blocks) and canvass the entire area for permitted and nonpermitted sites and invite every *nth* worker at each site to participate in the study.

Lessons Learned About LTS

Construction workers who participated in the reflection session confirmed our speculations that the electronic referral process is problematic and that in-person interactions would be more effective.

The LTS sample was designed to generate seeds from two populations: (1) a subset of members of the TLS sample and (2) a sample of day laborers. Although recruiting day laborers as seeds was very effective, some workers in both seed populations did not successfully recruit peers to participate in the study. This produced referral chains that were very short, with few penetrating beyond two individuals past the seed. The low referral rates could be due to the electronic referral system, which required respondents to provide contact information (e.g., phone number, email address) of those they wished to refer. Respondents may have been uncomfortable providing this information or may simply not have it (e.g., individuals who work together do not necessarily know how to contact one another outside of the job site). Moreover, individuals who were recruited in person by the field team were immediately presented with a physical gift card, but those who were referred only had the option for an electronic gift card because all contact with the study team was electronic. Even when respondents provided contact information for their peers, few of the referrals completed the survey. When they received the outreach text or email from the research team, it may have been flagged as spam or they may not trust clicking a link from an unknown number or email. For this population, in-person recruitment and explanation of the study may be critical to build trust and secure buy-in. Our experiences suggest that, even among socially networked populations, a referral-based sample may not be effective.

IMPLICATIONS FOR POLICY AND PRACTICE

Construction Industry

Prior research has suggested that labor trafficking and other labor abuses are common in the construction industry, and this study confirms those findings. One limitation of this study is that the survey instrument did not capture nuanced information about the various forms that employment in construction can take, including work for a primary contractor or subcontractor or classification as an employee or independent contractor. Although beyond the scope of this study, prior research has suggested that labor abuse in construction is due, at least in part, to an abundance of workers classified, sometimes inaccurately, as independent contractors rather than employees, which limits their eligibility for some labor protections (Galemba, 2023). Future research is needed to better understand how legal and regulatory standards relate to the prevalence of labor trafficking and other labor abuses in the construction industry.

Service Providers

One limitation of this study is that we did not ask about service needs, help-seeking, or the longer-term impacts of labor abuse. Although service needs and receipt were not a focus of this study, outreach and marketing of services for individuals who experience human trafficking often cater to female clients and are not gender-responsive to males (National Human Trafficking Training and Technical Assistance Center, n.d.). In this study, most individuals who experienced labor trafficking identified as male. Other research has discussed the impact that labor abuses, such as wage theft, have on construction day laborers in the short, medium, and long terms, including housing instability, mental and physical health problems, and substance abuse (Galemba, 2023). It is important to ensure that services are available to support the healing and recovery for everyone who has experienced human trafficking and other labor abuses, regardless of age or gender.

Law Enforcement and Regulatory Agencies

Labor abuses that are enforceable by the Department of Labor's Wage and Hour Division and the Occupational Safety and Health Administration are common in construction. For example, many respondents experienced a range of poor working conditions, including being made to be available day and night without adequate compensation (20%), experiencing wage theft (13%), and completing hazardous services without proper protective gear (13%). Although these abuses alone do not necessarily constitute labor trafficking, monitoring by the appropriate regulatory agencies is needed to ensure safe and just workplaces. If these forms of abuse and exploitation were more proactively identified and responded to, regulatory agencies may also uncover cases of potential labor trafficking that could be referred to law enforcement for further investigation.

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APPENDIX: DERIVATION OF TLS AND LTS WEIGHTS

Approximations to Selection Probabilities

Data collection for the time-location sample (TLS) captured two sets of respondents, namely those found at either a selected or unselected site. Sample selection was therefore modeled as arising from one of two stratified multi-stage sampling designs, detailed as follows:

The study region was partitioned into 14 zones, and sampling was carried out independently for each zone. Therefore, each zone was treated as an individual stratum.

Stage 1 Selection Probabilities

For the respondents observed at selected sites, the stage 1 selection probabilities are calculated as follows: Let RS refer to a selected site and $RS\ selected$ refer to a selected site that was selected for the sample. In a number of cases, selected sites selected from the frame were found to have a complete absence of workers present at the site. Let $RS\ empty$ refer to such sites, and RS observed refer to those found to have workers present at the site. Hence, stage 1 selection probabilities are decomposed as

$$P(RS\ selected\ and\ observed) = P(RS\ selected) \times P(RS\ observed\ |RS\ selected).$$

We adopt the following notation. Let:

i. be the number of selected sites on the sampling frame for the corresponding zone,
ii. be the number of selected sites selected from the sampling frame for the corresponding zone, and
iii. be the number of such selected sites that were observed to have an absence of workers at the site, and hence - be the number of such selected sites that were observed to have a presence of workers at the site.

For the first component, $P(RS\ selected) = n_{RS}/N_{RS}$, and for the second component, $P(RS\ observed \mid RS\ selected) \approx (n_{RS} - n_{RS,0})/n\_{RS}$; a simple approximation was used for the second component, as site information that could serve as covariates in a nonresponse modeling scheme proved difficult to capture across all selected sites. Therefore,

$$P(RS\ selected\ and\ observed) = \frac{n_{RS}}{N_{RS}} \times \frac{(n_{RS} - n_{RS,0})}{n_{RS}} = \frac{(n_{RS} - n_{RS,0})}{N_{RS}}.$$

For the respondents observed at unselected sites, the stage 1 selection probabilities are calculated as follows. Let US refer to an unselected site. Given the search radius around selected sites that are found to be absent of workers, it was assumed that each accessible unselected site was "attached" to only one selected site. Let RS' refer to that selected site to which the US site was attached.

Similar to the case with the visited selected sites, several unselected sites were found to have an absence of workers present at the site. Let $US\ observed$ refer to an unselected site that was selected and found to have workers present at the site. Stage 1 selection probabilities are decomposed as follows:

$$\begin{aligned} P(US\ selected\ and\ observed) &= P(US\ selected) \times P(US\ observed \mid US\ selected) \\ &= P(RS'\ selected\ and\ empty) \times P(US\ observed \mid RS'\ selected\ and\ empty) \\ &= P(RS'\ selected) \times P(RS'\ empty \mid RS'\ selected) \\ &\quad \times P(US\ observed \mid RS'\ selected\ and\ empty). \end{aligned}$$

Based on the notation given above,

$$P(US\ selected\ and\ observed) \approx \frac{n_{RS}}{N_{RS}} \times \frac{n_{RS,0}}{n_{RS}} \times \frac{n_{RS}-n_{RS,0}}{n_{RS}} = \frac{n_{RS,0}}{N_{RS}} \times \frac{n_{RS}-n_{RS,0}}{n_{RS}}.$$

A simple approximation was used for the third component and based on the percentage of selected sites that were found to have workers as the pertinent information could not be collected for unselected sites.

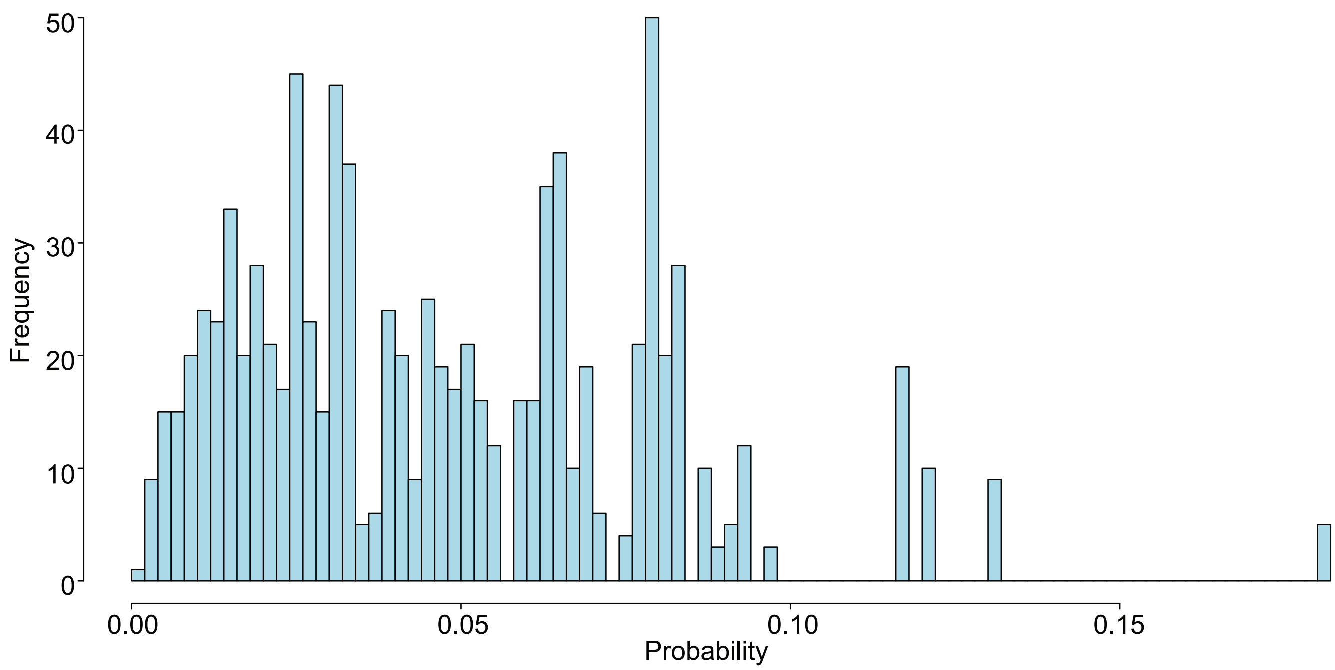
Stage 2 Selection Probabilities

For both selected and unselected sites, the stage 2 selection probabilities are evaluated as the ratio of the number completed interviews against the estimated count of the number of workers present at the site.

Final Selection Probabilities

The final selection probabilities are taken to be the product of the stage 1 and 2 selection probabilities. **Exhibit A-1** presents a histogram of these probabilities for the 903 respondents.

Exhibit A-1. TLS Selection Probabilities

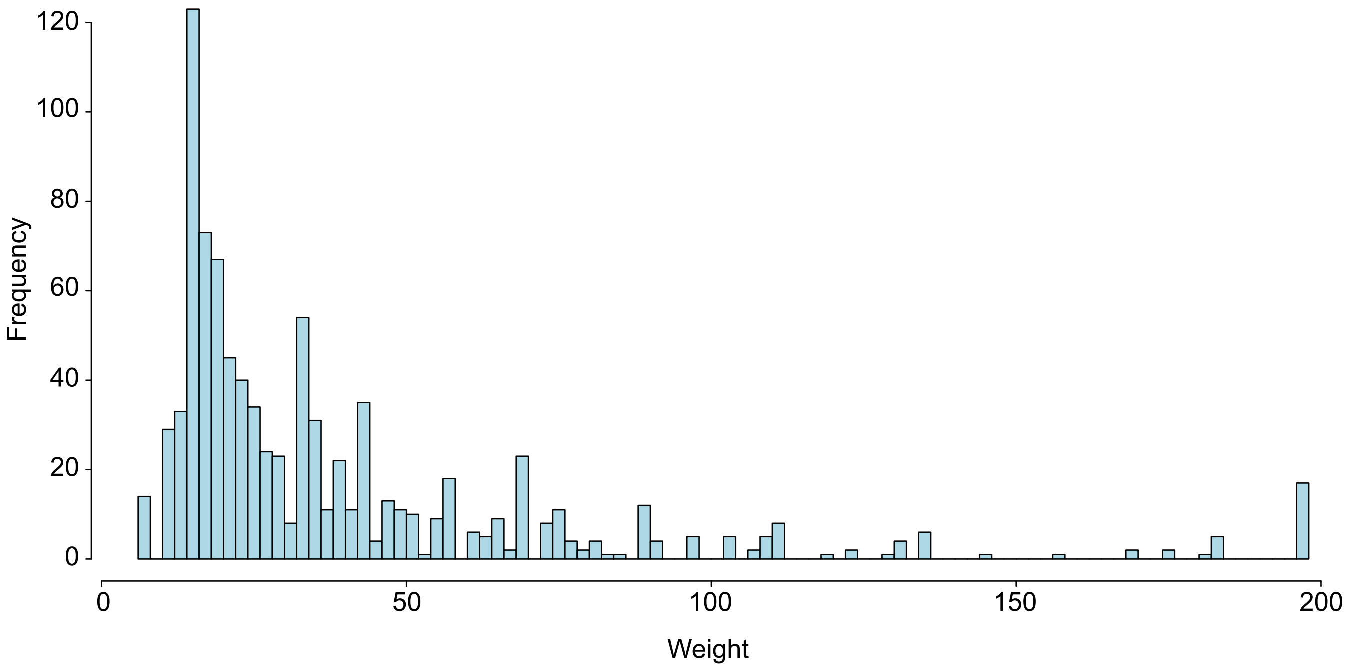


The mean of the selection probabilities corresponding to respondents from the selected and unselected sites respectively was 0.056 and 0.040. Respondents from unselected sites typically have smaller selection probabilities as these are conditional on first selecting the corresponding selected site and hence there was an additional layer of randomization.

Approximations to Sampling Weights

Sample weights are based on the inverse of the sample selection probabilities. Some selection probabilities are relatively small, resulting in extreme weights that consequently could be driving the estimates. As suggested by Battaglia et al. (2004), the sample weights are trimmed at the upper end at five times the mean of the weights and the lower end at one-fifth the mean of the weights. **Exhibit A-2** gives the final trimmed sampling weights. The mass at the upper end corresponds to the extreme weights that were trimmed.

Exhibit A-2. TLS Sampling Weights after Trimming



Estimation

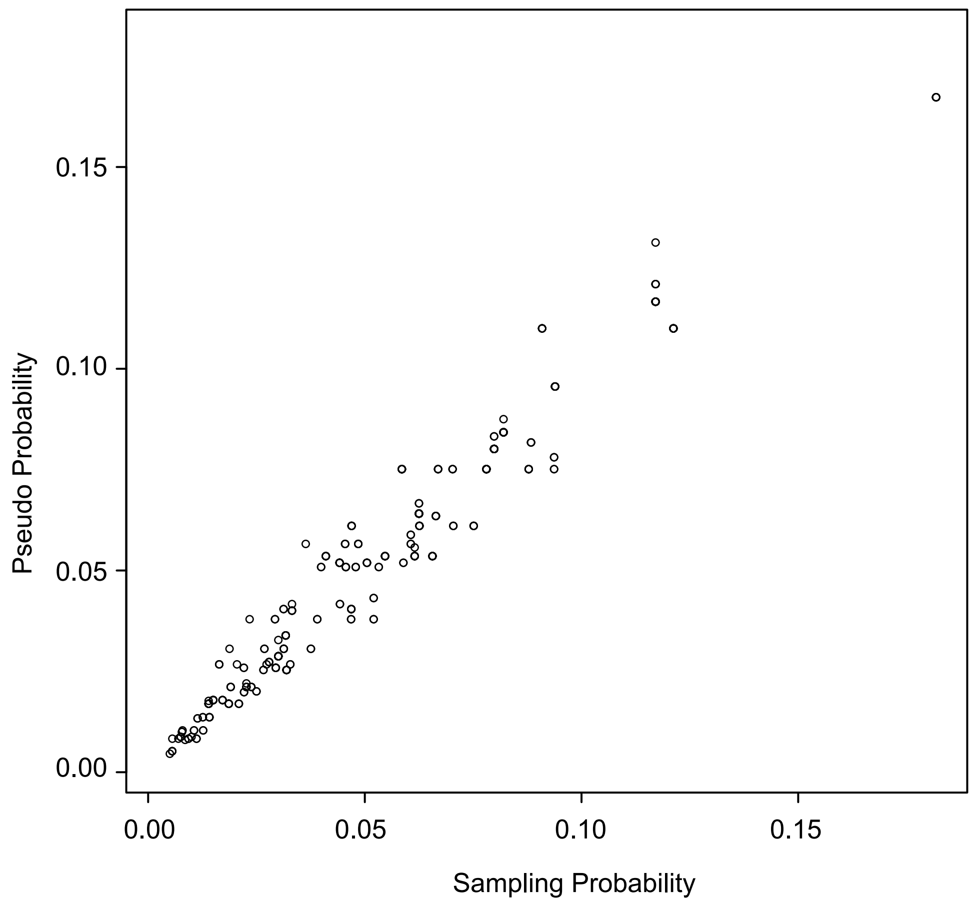
Point estimation was based on the weighted average of the survey responses. For the purposes of variance estimation, given the inherited difficulties with determining finite population correction factors through the multistage design and conditional selection probabilities, sampling was treated as a with-replacement design. Variance estimates are based on the traditional linearization approach.

Statistical Matching Exercise for TLS Respondents

A comparison analysis based on a statistical matching exercise is used to determine whether the results support the argument that the approximated weights are appropriate for the respondents observed at unregistered sites. The exercise is outlined as follows.

As recommended by Elliot and Valliant (2017), a beta regression model is used to first impute pseudo probabilities for all respondents where the evaluated selection probabilities corresponding to the respondents observed at the registered sites serve as the reference probabilities. An array of covariates is considered, and a stepwise approach is used to select an appropriate subset of variables to use in the model. The variables retained for the model are the zone of the corresponding site, disability status, gender, and ratio of number of workers present at site to number interviewed (this variable is treated as categorical with five levels based on cut points at 0, 1, 2, 5, 10, and 10+). The model is found to give a satisfactory fit based on a likelihood ratio test against the full main effects model. **Exhibit A-3** provides a scatterplot of the probabilities based on the design and the imputed probabilities for respondents found at registered sites. The linear trend is apparent in the plot, indicating close agreement between the two vectors.

Exhibit A-3. Scatterplot of Evaluated Selection Probabilities and Imputed Probabilities for TLS Registered Site Respondents



The correlation measure between the probabilities based on the approximated design and the imputed probabilities for respondents found at unregistered sites is 94.2%. The difference in the estimates for the labor trafficking variables are negligible when using the imputed probabilities for the unregistered site observations. These findings support the notion that the originally calculated weights, taken to be the inverse of the selection probabilities, for respondents found at unregistered sites are suitable for estimation purposes. Further, the statistical matching procedure should be explored for assigning pseudo weights to the network sample respondents.

Statistical Matching for Network Sample Respondents

The statistical matching procedure used to impute pseudo weights for the network sample respondents is adopted from that used for the TLS-based exercise. The same set of covariates are used in a preliminary beta regression model, and the stepwise selection procedure, results in retaining the zone of corresponding site, gender, disaster site worker status, and ratio of number of workers present at site to number interviewed. The model is found to give a satisfactory fit based on a likelihood ratio test against the full main effects model. **Exhibit A-4** provides a scatterplot of the evaluated selection probabilities based on the design and the imputed probabilities for all TLS respondents.

Exhibit A-4. Scatterplot of Evaluated Selection Probabilities and Imputed Probabilities for All TLS Respondents

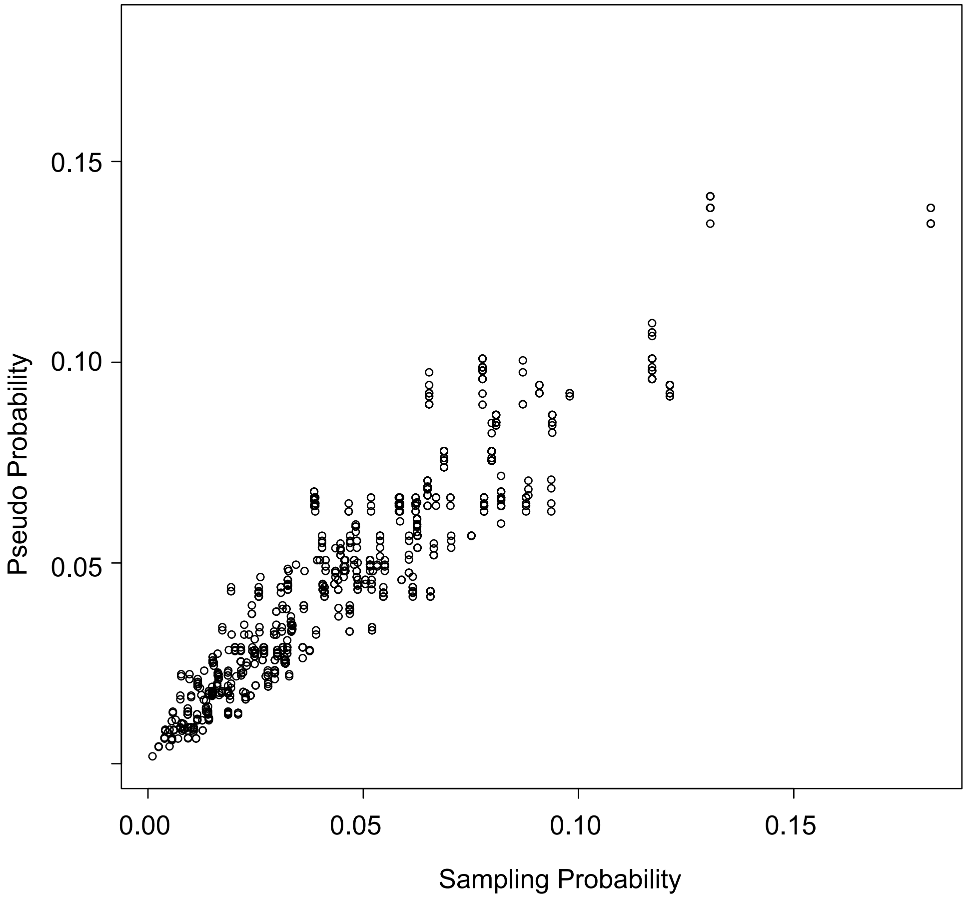
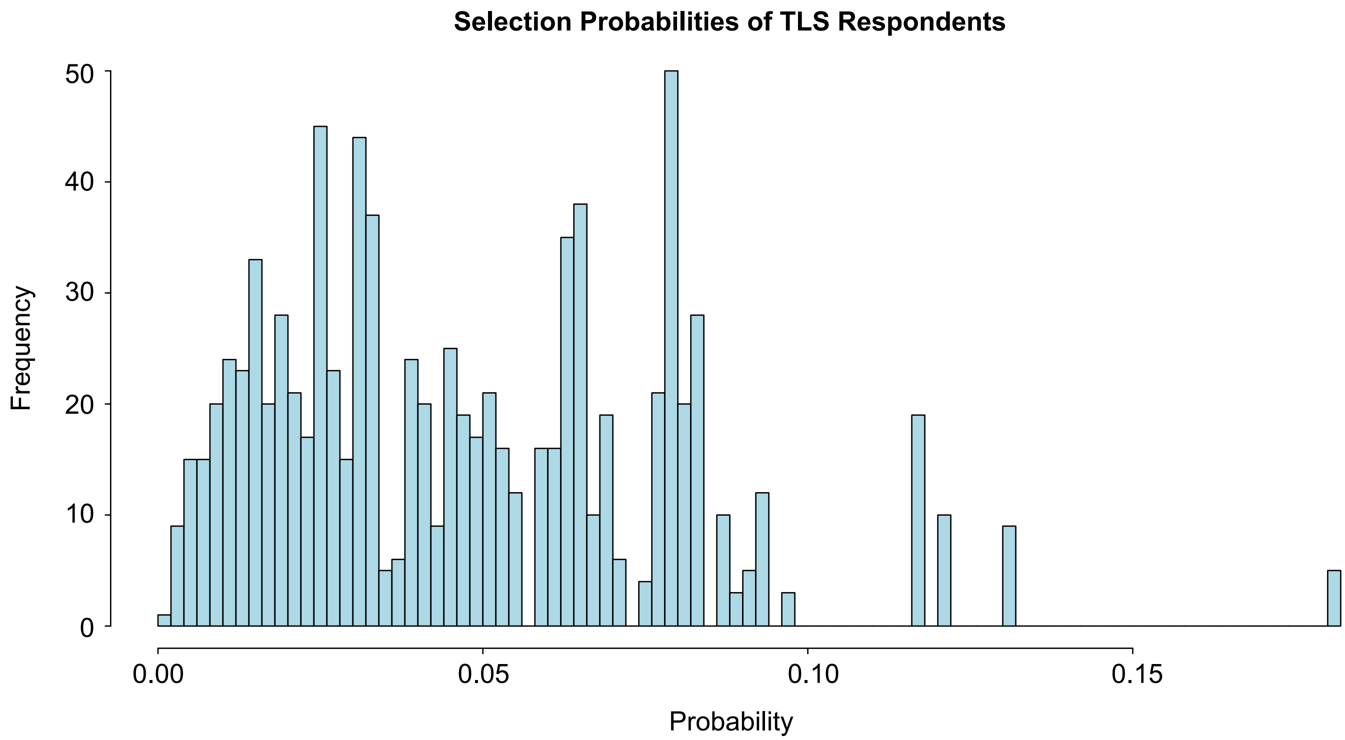
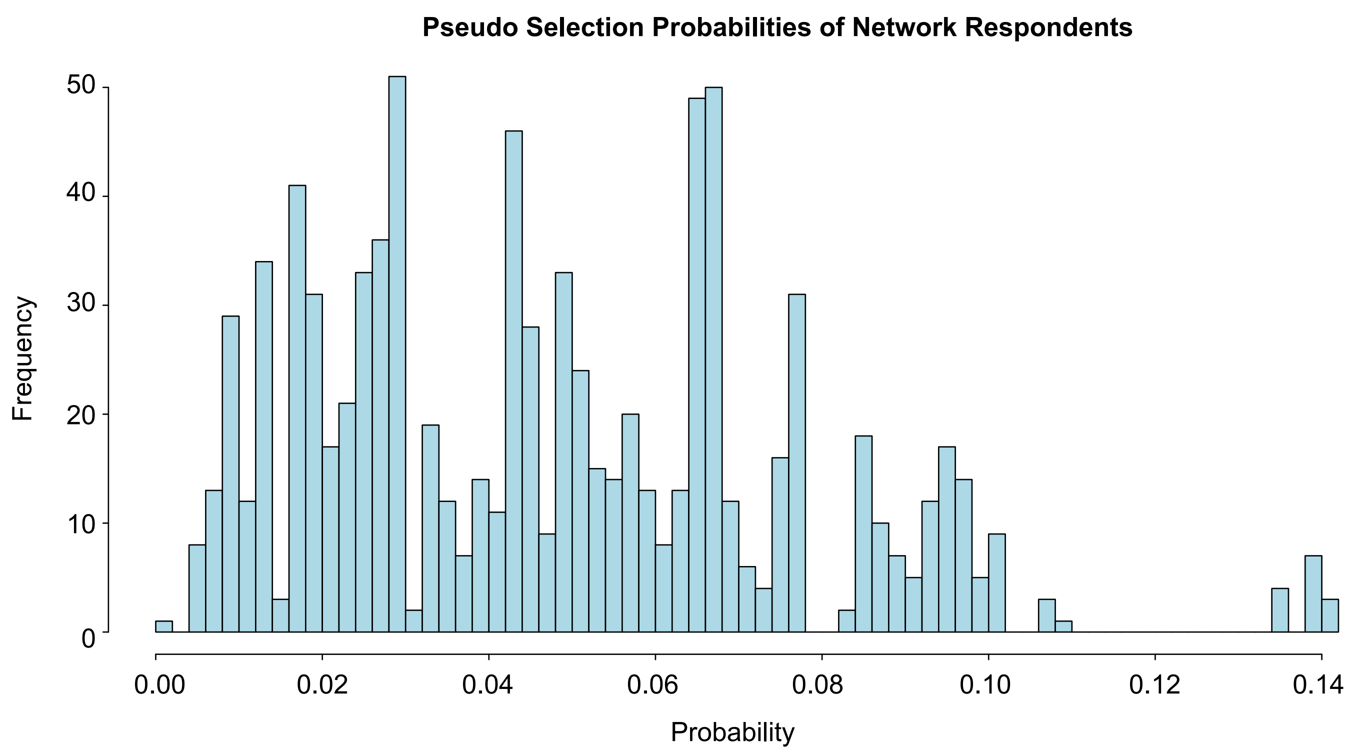


Exhibit A-5 presents histograms of the evaluated selection probabilities for the TLS respondents and the imputed selection probabilities for the network sample respondents, respectively. The close agreement in the distributions is due to the TLS respondent selection probabilities serving as the reference values for assigning the network sample pseudo probabilities.

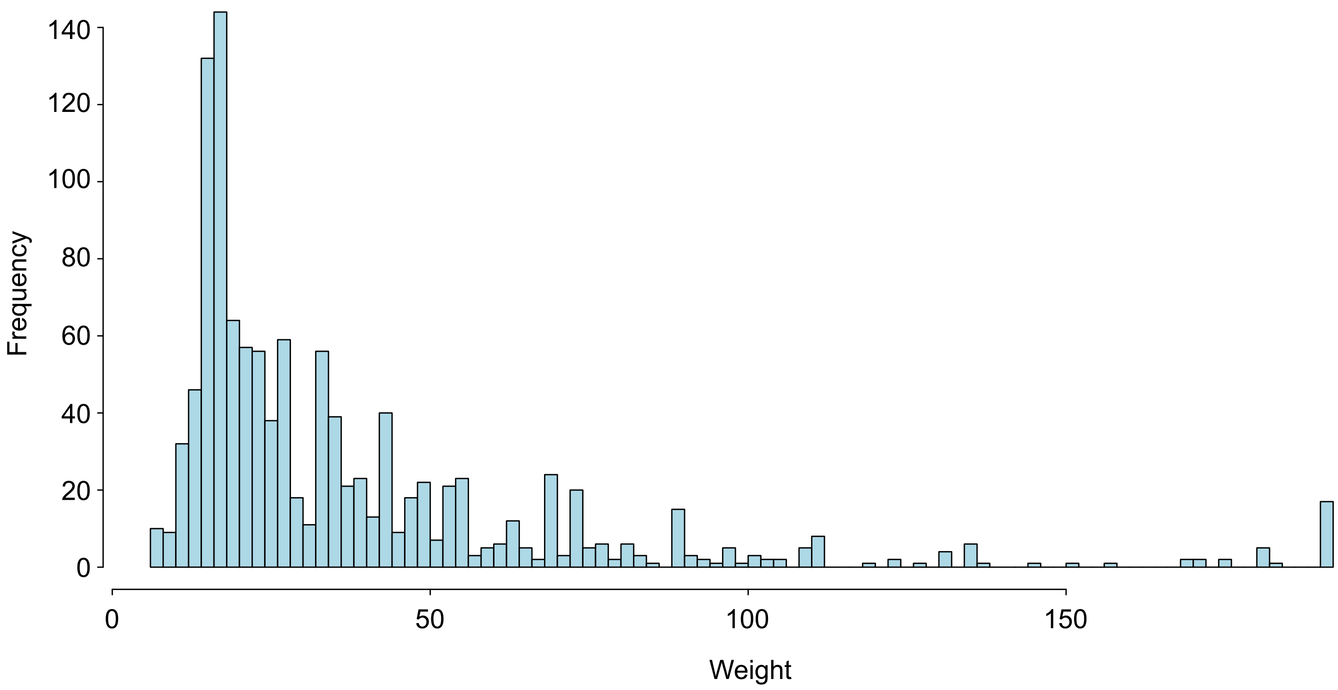
Exhibit A-5. Histograms of the Evaluated Selection Probabilities for the TLS Respondents and Imputed Selection Probabilities for the Network Sample Respondents, Respectively





The inverse of the evaluated selection probabilities for the TLS respondents and the imputed selection probabilities for the network sample respondents serve as the sampling weights. As some of the weights are considered extreme, these are trimmed at the upper end at five times the mean of the weights and at the lower end at one-fifth the mean of the weights. **Exhibit A-6** presents a histogram of the final trimmed sampling weights for the full sample. The mass at the upper end corresponds to the extreme weights that were trimmed.

Exhibit A-6. Final (Pseudo) Sampling Weights for TLS and Network Sample Respondents



Limitations

The TLS design was oriented about observing registered construction sites. A search for nearby unregistered construction sites was made when an absence of workers was observed at selected registered sites. For extrapolation purposes, it must be assumed that nearly all unregistered sites are within range of a registered construction sites. Some unregistered sites may be situated outside of the search radius of all registered sites, and this is reported as a limitation in this study. Future studies may benefit from augmenting the current design with a grid-selection approach that maps out all unregistered sites in selected areas.

Selection and observation took a staggered approach over the course of a year, where zones were observed based on the month of observation. For extrapolation purposes, it must be assumed that the population of construction workers remained homogeneous within each zone and over the course of the year. This assumption may have been violated with seasonal work effects and weather interruptions.

The network sampling design was likely reaching away from construction workers and into a part of the working population whose primary type of work may have been misconstrued to be construction (e.g., fence building or construction site cleanup). The sample observed at the construction sites (i.e., TLS design) and the sample obtained through the network sampling design were found to have a markedly different composition in terms of the variables related to labor trafficking, gender, education, disaster, and born in the United States, among others; Wald-type hypothesis tests were found to give a highly significant p-value for each of these variables. For these reasons, we have opted to provide disaggregated estimates by sample type (i.e., TLS and network) with the interpretation that the TLS design provides estimates for the population whose primary type of work is construction, whereas the network design provides estimates for the population whose type of work include other sectors.

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