ABSTRACT

ABBASI, MUHAMMAD HAMMAD. Can We Use Workers' Feedback Crowdsourcing to Protect Apparel Factories and Brands from Reputational Damage? (Under the direction of Dr. Lori Rothenberg and Dr. Robert Handfield).

Unsafe working conditions provided by the suppliers of apparel brands lead to worker strikes and factory accidents. These events can result in a wide range of problems such as stock-outs, long lead-times, failure to meet customer demand, upsurges in costs and damage to brand reputation. To avoid reputation, damage many brands adopted a code of conduct. Brands used a factory audit process to verify whether suppliers met their code of conduct. Lack of frequent information sharing between supplier and brand, dependency on unqualified auditors, resource constraints of brands, inconsistent factory audits, low worker participation, and lack of freedom of association (FOA) protection restrict existing factory audit practices necessary for obtaining real-time visibility of apparel factory working conditions and for reducing the frequency of negative news headlines.

The concept of workers feedback crowdsourcing based on the “workplace feedback system” (WFS) is proposed to address the real-time visibility gap offered by existing factory audit practices. WFS is a communication platform with which factory workers can use cell phone technology to answer pre-recorded surveys and record workplace grievances. This dissertation was the first empirical study that used workers feedback crowdsourcing data to answer the research question: Can we use workers' feedback crowdsourcing to protect apparel factories and brands from reputational damage? Two research objectives were investigated to answer the research question. First was to determine the association of factory characteristics (i.e., workers grievances and factory indicators) with the negative publicity of apparel factories in Bangladesh for the year 2016. Second was to identify the differences between factories that

received negative publicity and those that did not, based on factory characteristics. For negative publicity, publicly available news articles were searched using both local Bangladeshi and international news publishers, from Jan 1, 2016 to Jan 30, 2017.

Numerous techniques were used to investigate the research objectives: stepwise logistic regression, exact logistic regression and bootstrapping using stepwise logistic regression along with worker responses and bar charts frequency plots. Forced overtime, FOA, long working hours, cooperative approach to inspection, and buyer-supplier relationships were the factory characteristics that were associated with the negative publicity of apparel factories based on the findings of the first research objective. Forced overtime, FOA, and long working hours were consistent with the findings of the second research objective where open-ended responses were analysed to determine the most frequent issues faced by workers among factories receiving negative publicity.

Furthermore, the triggering factors of negative publicity highlighted by local and mainstream media somewhat contradicted the issues faced by workers among the factories receiving negative publicity. Forced overtime was the only issue mentioned by both workers and the news media. Fire safety was the most frequent trigger of negative publicity mentioned by the news media but was missing on the frequent issues faced by workers among factories receiving negative publicity.

In summary, this dissertation presents a strong case for leveraging workers feedback crowdsourcing to understand apparel factory working conditions in real-time and to limit the reputational damage of apparel factories. The findings also suggest the need for a more comprehensive inspection approach, apart from relying solely on worker crowdsourcing feedback. A proposed solution to the problem is to use factory audit reports that complement the

newly proposed data source to gain a more comprehensive picture of the apparel factory working conditions and to protect from negative publicity.

Can We Use Workers' Feedback Crowdsourcing to Protect Apparel Factories and Brands from Reputational Damage?

by
Muhammad Hammad Abbasi

A dissertation submitted to the Graduate faculty of
North Carolina State University
in partial fulfilment of the
requirements for the degree of
Doctor of Philosophy

Textile Technology Management

Raleigh, North Carolina
2018

APPROVED BY:

Dr. Lori Rothenberg Committee Co–Chair	Dr. Robert Handfield Committee Co–Chair
Dr. David Dickey	Dr. Marguerite Moore

DEDICATION

I dedicate this research to my parents, Mr. Abid Ali Abbasi and Mrs. Shamim Akhter, for giving me the freedom to pursue my journey; to my uncle, Dr. Rashid Abbasi, for believing in me and supporting me to pursue my American dream; and to my friend, Mr. Hamza Qureshi, for being my pillar of strength during the tough phases of my life in the United States. Thank you and I love you all for being a part of my journey.

BIOGRAPHY

Muhammad Hammad Abbasi was born in Karachi, Pakistan's biggest city. He is the third of four children to Mr. Abid Ali Abbasi and Mrs. Shamim Akhter. In 2007, Hammad graduated from Govt. Degree College Malir Cantt with his high school diploma. He accepted an admission offer to one of the finest textile universities in South Asia, National Textile University (NTU) in April of 2009, where he pursued a BS in textile engineering, graduating in 2013. Following his graduation, he worked for Soorty Enterprises, the second largest denim manufacturer of Pakistan, for 15 months to get some exposure to yarn manufacturing processes. Then he joined SBT Japan, one of the leading used car exporter in the world, as an international business development executive to get some business development exposure. He liked to be on the strategy side of the business and then decided to pursue a Dual Masters of Global Innovation Management (MGIM), jointly offered by Aix Marseille Graduate School of Management, France, and Jenkins Graduate School of Management, North Carolina State University, USA. At MGIM, he was exposed to different arenas of businesses (i.e., marketing, strategy, data driven decision making) and decided to get some exposure to the world of data science. Following his graduation, he accepted an offer as Data scientist intern at Centre for Innovation Management Studies. At this point of his career, he decided to pursue a career in the domain of data science and business analytics to solve social issues. He accepted an offer of fully funded PhD in Textile Technology Management from the College of Textiles under the supervision of Dr. Lori Rothenberg and Dr. Robert Handfield began work on a research project for one a leading apparel and footwear brand, under the supervision of Dr. Robert Handfield, to investigate the labor abuses in their global apparel supply chain. He leveraged his manufacturing and data science experiences to investigate the labor abuses in global apparel supply chain as part of his PhD

dissertation. In June 2018, he presented his PhD dissertation paper at the corporate sustainability conference at MIT, organized by ARCS, the most prestigious alliance for researcher in the domain of corporate sustainability. He looks forward to the world after his Ph.D.

ACKNOWLEDGMENTS

First, I would like to thank God for giving me the strength and courage to utilize many learning opportunities. I also would like to thank my parents and my siblings for pushing me to break barriers and for encouraging me to grow as human being. To Dr. Lori Rothenberg, for supporting my research and sharing valuable experiences. To Dr. Dave Dickey and Dr Shaina Race, for giving your valuable feedback. To XYZ, for sharing your valuable data. Finally, to my committee members, especially my co-chairs, Dr. Lori Rothenberg and Dr. Robert Handfield, thank you for your direction and pushing me to work hard. And to Dr. Lisa Carl and my friend Malaz, thank you for your support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

CHAPTER 1: OVERVIEW

1.1 Introduction and Motivation for the Study

Apparel brand domination over suppliers in the global value chain is caused by the structure that exists today in apparel supply chain. Apparel brands oversee high-value-based divisions (i.e., design, product development, and marketing), while outsourcing low-value activities to supplier factories (i.e., labor-rigorous manufacturing) (Locke, Amengual, & Mangla, 2009). Outsourcing to low-cost countries is a business strategy used by apparel brands dating back to the middle of the 20th century. Outsourcing enables brands to remain competitive in a cost-competitive apparel industry but at the cost of safe factory working conditions.

Labor disruptions such as worker protests and strikes can lead to a wide range of difficulties for brands including stock-outs, long lead times, failure to meet customer demand, and the brand damaged reputation. The news media can have a powerful effect on a brand reputation. In 2013, a series of building collapses and factory fires in Bangladesh, Pakistan, and Indonesia captured the headlines of mainstream newspapers such as *The New York Times* and *The Wall Street Journal*. The negative headlines posed a threat to the reputations of the apparel brands who outsourced their manufacturing. The news stories increased public awareness about unsafe factory conditions and led to activism and protests. According to a recent Supply Chain Management World (SCM) survey (SCM, 2015), 83 percent of supply chain executives, across different industries including apparel, were concerned about the risk of production disruption such as fire and strikes; 84 percent were willing to invest in fair labor standards to help prevent these problems.

Private or nongovernmental regulation emerged in the early 1990s to address unsafe working conditions in apparel factories, as local governments were either unable or unwilling to

regulate labor standards. Governments failed to enforce regulation for two major reasons: limited resources to enforce regulation, and fear of losing business due to regulatory enforcement (Locke et al., 2009; O'Rourke, 2003).

In response to pressure from activists in the early 1990s, brands adopted codes of conduct (Bartley, 2007) to which suppliers must adhere to remain in business. Most of the codes adopted by brands followed those of the International Labor Organization (Kaptein, 2004). Brands now use a factory audit process to verify whether suppliers meet the standards specified in the codes of conduct. Some of the issues covered in factory audits are health and safety, wages, working hours, freedom of association, discrimination, child labor, and forced overtime (Kaptein, 2004).

Scholars categorize factory audits as traditional compliance-based and commitment-based approaches to audits (Locke et al., 2009; Locke et al, 2013; Lund-Thomsen et al, 2014). The compliance-based approach to a social audit is an iterative process in which stakeholders employ accurate information from factory audits to exert pressure on brands to adopt codes of conduct. Brands then use this information to reward or penalize factories that are out of compliance.

Critics argued that the assumptions underlying a compliance-based approach (i.e., the power of brands, the role of audit information, and incentives for good labor practices) are not based on a realistic empirical ground (Locke et al., 2009; Locke et al, 2013; Lund-Thomsen et al, 2014). Critics also stated the real causes behind limited working condition improvements at apparel factories are resources and power constraints of buyers, inaccurate audit information regarding working conditions and failure to either penalize non-compliant factories or reward compliant factories. Brands that rely solely on compliance-based factory audit information could miss code violations which may later turn up in negative newspaper headlines.

The commitment-based approach to factory audit, on the other hand, is more effective when the auditor conducts multiple factory visits. The role of the auditor changes from inspector to engager. This engagement with suppliers leads to joint information exchange and troubleshooting to protect the mutual interests of all stakeholders.

Although the cooperative inspection does work for a few suppliers (Locke et al., 2009), it falls short in tracking the entirety of a supplier's overall working conditions because of the continuous work required on the part of the brand. In today's cost-competitive and lead-time focused apparel world, apparel brands often expect suppliers to handle most of the costs associated with labor issues (Lund-Thomsen et al., 2014; Yu, 2009).

A complementary monitoring method to factory audits is worker feedback crowdsourcing; based on the workplace feedback system which can ensure the continuous monitoring of workplace activities at the factory level, as opposed to the snapshot approach of factory audits. The workplace feedback approach provides factory workers a platform on which to record their grievances anonymously whenever they face abuse inside factories. The factory workers complete periodic cell phone surveys but can also use a toll-free phone number to immediately report abuse. Conceivably, a brand could obtain continuous information about the factory conditions using this system; traditional factory audits provide information every six to twelve months. This dissertation used workers feedback crowdsourcing based on the workplace feedback system to answer the main research question which is: Can we use workers' feedback crowdsourcing to protect apparel factories and brands from reputational damage?

1.2 Purpose and Objectives

The purpose of this dissertation was to empirically evaluate the workers feedback crowdsourcing to answer the main research question by investigating the association of factory characteristics

(i.e., workers grievances and factory indicators) with the negative publicity of apparel factories. The significance of this relationship has important implications. The proposed data source could be used in addition to compliance or commitment-based factory audits to obtain the most up-to-date information about factory conditions, which may further save brands from negative headlines.

The second objective was to identify the differences between factories that received negative publicity and those that did not, based on factory characteristics. These differences could occur because of the variability in issues faced by factories, the pattern of worker responses among negative factories and in the polarity of sentiments from workers open-ended feedback. This objective examined the triggers to the negative publicity.

1.3 Research Method

The unit of analysis was the apparel factory. All factories studied are located in Bangladesh. Workers in these factories responded to a pre-recorded cell phone survey between January 1, 2016 and December 31, 2016. Treating the apparel factory as the unit of analysis for this study is aligned with the primary objective of identifying factory characteristics that led to the presence or absence of negative headlines.

The sampling frame of this study was Bangladesh apparel factory workers survey responses. The apparel industry was chosen because of the increase in apparel factory accidents in the last five years, which has driven scholarly attention to labor issues across the global apparel supply chain. The number of factories included in the sample for this dissertation was 194. The sample corresponded to approximately 16,000 workers, based on a workplace feedback survey response rate of up to 1 percent per factory.

This dissertation used three data sources: (1) worker responses to cell phone surveys; (2) publicly available information on sample factories, and (3) news articles about Bangladesh apparel factories. Factory characteristics were determined by worker responses to survey questions about factory conditions and factory-level indicators. Publicly available news articles provided data on negative publicity.

XYZ, a third-party monitoring service provider, provided worker responses to the survey from the workplace feedback system. LexisNexis News Desk (LNND) was used to collect newsfeed data. Python and Base SAS were used to analyze data from news articles. Logistic regression was used to analyze the data.

1.4 Contributions to the Study

This dissertation used a new data source: workers feedback crowdsourcing based on a workplace feedback system. The workplace feedback system provided a continuous look at factory working conditions. The system may eventually be able to complement existing auditing processes. This dissertation did not attempt to propose an alternative to factory audits. The focus was on identifying factory conditions associated with negative publicity in the form of news headlines. However, a workplace feedback system may eventually be shown to provide the most up-to-date information about factory working conditions, thereby saving brands from negative publicity.

1.5 Organization of the Dissertation

This dissertation is organized in five chapters. Chapter 1 introduces the research objectives of the study. Chapter 2 provides a detailed overview of the existing literature on the monitoring of labor issues in the global apparel supply chain, approaches to factory audit along with criticism, and comparison of a proposed data source with existing audit practices. Chapter 3 presents and discusses the Labor Compliance Conceptual Framework, as well as this dissertation's research

design and methodology, including research objectives, sampling frame, and data collection procedures. Chapter 4 presents the detailed analysis from investigating both research objectives. Chapter 5 presents the results, discussion, conclusion, implications, and potential areas for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter includes a detailed overview of the existing literature on the monitoring of labor issues in the global apparel supply chain. The chapter starts with a historical overview of regulation enforcement to ensure monitoring, then discusses approaches to factory auditing, and covers criticisms regarding the current auditing process. Secondly, a new data source is proposed and compared to existing factory audit approaches, and then the significance of brands publicity is discussed. Finally, the worker- and factory-level indicators that impact factory working conditions are discussed.

2.1 Regulatory Enforcement and Monitoring Models: An Overview

Private monitoring institutions emerged in the early 1990s when brands and retailers were accused of allowing or ignoring poor working conditions in their suppliers' factories. Private monitoring is also called compliance model, private voluntary code of conduct, or private/nongovernmental voluntary regulatory system in the existing literature (Anner et al., 2013; Lund-Thomsen et al., 2014; O'Rourke, 2003).

In the absence of international regulatory monitoring institutions, private monitoring institutions led efforts to regulate global labor standards. The governmental regulatory system failed to enforce regulation for two major reasons (O'Rourke, 2003): limited resources to enforce regulation, and fear of losing business due to regulatory enforcement (Locke et al., 2009). Private monitoring institutions are based on voluntary labor standards which set a code of conduct, or minimum guidelines, for evaluating apparel factory performance.

A code of conduct provides brands with a means to secure workers' labor rights in their supply chain (Keller, 2008). Further, it specifies minimum standards for factory working conditions. Most of the codes adopted by brands use internationally accepted conventions such

as those of the International Labor Organization (Kaptein, 2004). Codes of conduct are now a globally accepted approach to addressing labor practices. These have become a dominant tool for brands to handle the risk of labor abuse in their supply chains (Mamic, 2005).

O'Rourke (2003) describes private regulation enforcement in the context of internal, external monitoring, and verification. Internal monitoring includes the inspection of suppliers conducted by their brands and retailers. External monitoring includes third-party service providers such as Social Accountability International (SAI), Worldwide Responsible Accredited Production (WRAP), and the Fair Labor Association (FLA). Verification refers to the independent evaluation of a brand's social performance after being monitored by an independent (third-party) service provider such as Worker Rights Consortium (WRC).

2.2 Existing Factory Audit Approaches

Brands typically use two methods of control to manage labor violations (Chen L. &., 2016). The first identifies the problem by detecting labor violations through instruments such as certification and factory audits. The second aims to change supplier behavior by offering incentives such as training programs and performance bonuses. Certification help screen suppliers by identifying unethical factory management processes. Then, factory audits are used to ensure whether suppliers are adhering to the code of conduct. Finally, contingency payments penalize the supplier if any violations are detected during the audit process.

Factory audits are the primary tool used by brands to verify the adoption of codes of conduct and detect subsequent improvements in working conditions (Egels-Zandén, 2015). Factory audits adopt a snapshot approach to verification. The practices assessed in these audits include abuse, poor wages, excessive working hours, hazardous working conditions, and a lack of freedom of association (FOA) (Kaptein, 2004).

The factory audit involves an auditor spending a portion of his or her day on the factory floor, observing possible code violations and reporting them in the form of an action plan. Later, an auditor returns for a follow–up visit (Locke et al., 2009). The cadence for an audit is usually yearly. The auditor's level of training, the nature of the supplier-buyer relationship, and other factory-specific factors influence the results of the traditional auditing process (Short, Toffel, & Hugill, 2016). Scholars categorize factory audit in the context of the way it impacts improvements in working conditions (Frenkel et al., 2002; Locke et al., 2009; Locke et al., 2013; Lund-Thomsen et al., 2014).

2.3 Traditional Compliance-Based Audit

In a traditional compliance-based audit approach (Frenkel et al., 2002; Locke et al., 2009; Locke et al., 2013; Lund-Thomsen et al., 2014), actors such as activists, students, and consumers put pressure on brands to improve factory working conditions. Brands responding to external pressure adopt codes of conduct and then conduct factory audits to ensure that suppliers adhere to said codes. A supplier's tendency to adhere to the brand's code of conduct influences the supplier's chances of becoming a long-term and consistent vendor. However, if the supplier cannot meet the guidelines set by the brand's code of conduct, the supplier may lose orders with the brand (see Figure 2.1).

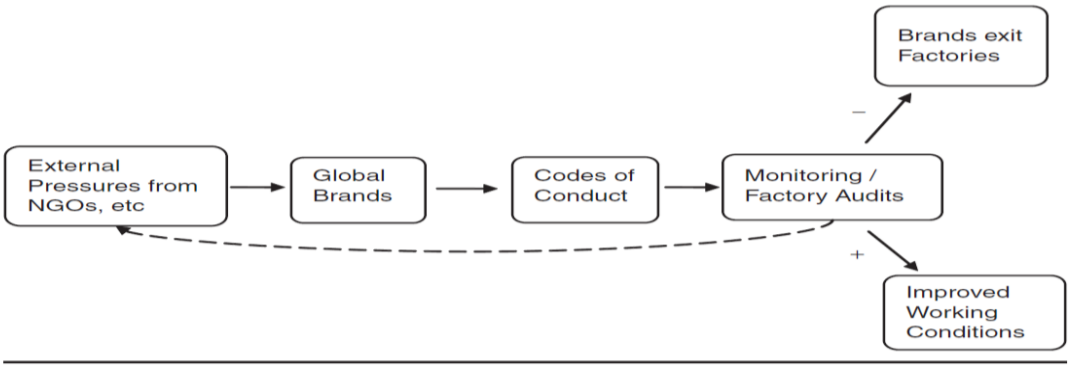


Figure 2.1. Traditional Compliance-Based Model (Locke et al., 2009)

2.3.1 Assumptions Underlying Traditional Compliance-Based Model

Both proponents and critics of traditional compliance-based audit make three assumptions regarding monitoring apparel factory working conditions (Locke et al., 2009; Locke et al., 2013; Lund-Thomsen et al., 2014). The first relates to the overall "power" of the brand. Brands can force suppliers to comply with labor standards in the same way they impose commercial terms and product quality parameters on the entire supply chain.

The second assumption relates to how information generated by factory audit influences the conduct of stakeholders (i.e., brands, activists, and suppliers). Information from a factory audit can have profound implications. Consumers use information from non-brand sources to hold brands responsible; activists use the information published by brands as a reference for verification. Thus, the accuracy of information plays a critical role in shaping the behavior of brands, suppliers, and external monitors.

The final assumption is that incentives are required to motivate stakeholders to modify behaviors leading to improvements in labor standards. This assumption implies the idea that compliant, anti-sweatshop factories will benefit, while non-compliant, sweatshop factories will pay the price in reduction or termination of orders.

To sum up, the traditional way of conducting a compliance-based factory audit is an iterative process in which stakeholders use accurate information from factory audits to exert pressure on brands to adopt codes of conduct. Brands then use this information to reward or penalize factories that are out of compliance.

Locke et al. (2009) empirically examined and argued that false assumptions are the real causes behind limited working condition improvements at apparel factories in which, in practice. The buyer lacks resources and/or power, audit information about working conditions is

inaccurate, and factories are neither penalized nor rewarded. This issue will be discussed in detail after the following discussion of three famous factory audit failures.

2.3.2 Limitations of Traditional Factory Audit Models: Cases of Failure

Three famous factory audit model failures in recent times are The Rana Plaza incident in Bangladesh, The Ali Enterprise factory collapse in Pakistan, and The Hansae sweatshop factory in Vietnam (Brown G. , 2017). In September 2012, 289 factory workers died in The Ali Enterprise factory collapse, three weeks after the factory received an "SA 8000" certification by an Italian service provider. In April 2013, The Rana Plaza building collapsed, killing more than 1,000 workers. Bureau Veritas (BV) inspected the building in 2011 and 2012 and certified it as a "Safe Factory." Four survivors of The Rana Plaza incident sued both BV and the buyer in a Canadian court. BV argued that it only accessed factory issues that were requested by the client. This demonstrates the critical role of buyer attitude in addressing labor issues.

The most recent case of factory audit failure was an unsafe working condition disclosure at the Hansae Vietnam complex. The complex. which employs more than 10,000 garment workers, underwent more than 26 factory audits in 2015. However, in the fall of 2015, workers started striking to protest poor working conditions. Following the strike, in October 2016 and July 2016, third-party service providers such as the Worker Rights Consortium (WRC) and the Fair Labor Association (FLA) conducted inspections and found serious health and safety violations. WRC was the first inspector to detect said violations, because of its unique inspection protocol, in which auditors rely on direct information from factory workers gleaned via on-site and/or off-site interviews.

A case study carried out on ABC brand (Locke et al., 2009) found conditions where audits were failed. Locke et al. (2009) observed that the auditor faced many difficulties in

gathering accurate and comprehensive information while inspecting working conditions at apparel factories. Difficulties included but were not limited to the factory audit process, auditor skill set, and resource constraints on the inspectors. These difficulties made factory audit information incomplete, inaccurate, and biased.

The first criticism on the traditional factory audit process from Locke et al. (2009) is that the factory audit is often based on a checklist which contains information such as attendance records and employee pay stubs. Auditors spend just one day during the factory visit reviewing the physical and documentary (the documentation of conditions) aspects of the workplace. Auditors have limited time to check factory documentation, physically inspect the factory, and discuss possible code violations with factory workers. This implies that traditional factory audit information is more representative of factory documentary records and less representative of actual working conditions.

The next criticism of the traditional factory audit process is the actual frequency of the audits. Most factories conduct annual audits. This restricts the audit's ability to assess important factors such as changes in intensity of the work cycle during high- and low-demand seasons. An auditor's prior professional experience and training play a huge part in helping the auditor comprehend important information during the audit process. Based on an analysis of 17,000 supplier audits from 2004 to 2009, Short et al. (2016) found that auditors are less likely to report code violations if they are less experienced, less trained, have audited the factory before, are paid by the audited supplier, or are part of an all-male auditing team.

As per Locke et al. (2009), auditors tended to identify issues related to employee wages, overtime employment, and factory safety. Consequently, they were less successful in identifying worker-management relation problems and freedom of association issues. Locke et al. (2009)

believed this was happening because most auditors came from either a human resources or operations background which hindered their ability to identify issues that, although they were becoming a major cause for concern, were not as easily identified as others.

Factory audits also may lead to a lack of freedom of association (FOA) protection. A FOA violation detection could pose a major cause for concern for the factory. Locke et al. (2009) found worker responses on this topic to be minute. Factory management claimed that most workers did not want unions; in some cases, the buyer was not aware that there was a union presence in its supplier's factory. Numerous empirical studies also witnessed the lack of FOA detection in the compliance-based audit approach. For instance, Anner (2012) conducted an empirical study that analyzed 805 factory audit reports published by the Fair Labor Association from 2002 to 2010. He found that factory audits detected only a 5 percent FOA violation (despite FLA strong emphasis on the detection of FOA violations), compared to a 40 percent violation detection in workplace safety and 30 percent detection in low wages. He then compared the findings of FLA with other existing compliance scores and found that all issues detected by FLA were correlated with the existing compliance scores except FOA. Anner (2012) concluded that lack of FOA detection is the result of FLA's inadequate factory audit process.

Similarly, Egels-Zandén et al. (2015) found, by analyzing 43 garment factory audit reports published by Fair Wear Foundation, that factory audits detected FOA violations in less than 5 percent of the factories. O'Rourke (2000) assessed the auditing practices of PricewaterhouseCoopers (PwC), one of the largest private inspectors of labor practices in 1999. The assessment includes more than 6,000 audit reports, including audits of Nike, Gap, and Walmart from factories in China and South Korea. O'Rourke (2000) found that PwC audits failed to detect major flawed labor practices such as harmful chemical use, violation of overtime

and wage laws, lack of FOA protection, and falsified timecards to hide unpaid overtime. These studies show the failure of the factory audit process to detect FOA violation.

The last criticism relates to how information collected through factory audits is incorporated into decision making. The three cases: The Rana Plaza incident, the Ali Enterprise factory fire, and the Hansae Vietnam workers strikes, as discussed above, show that incidents occurred even after factory audits were conducted. Eventually, a lack of information and inaccurate and unnecessary data from factory audit process lead to negative publicity for the associated brands.

2.4 Commitment-Based Approach to Audit

Instead of just imposing sanctions (i.e., termination of order) based on the findings of a social audit, the commitment or cooperative-based approach to auditing continuously tracks suppliers' factories by gathering information to engage factory management until workplace issues are solved in a cost-effective and sustainable way (Locke et al., 2009). This bottom-up, commitment-based approach to improving working conditions (Lund-Thomsen et al., 2014) is often even more effective when the auditor conducts multiple factory visits. The role of the auditor changes from "inspector" to "engager." The engagement with suppliers leads to joint information exchange and troubleshooting to protect the mutual interests of all stakeholders.

The commitment-based approach incorporates multiple steps, including noting the purchasing practices of buyers, conducting frequent information exchanges among buyers and suppliers, investing and building supplier capability (i.e., worker training), hiring demographically aware auditors, and conducting worker interviews both on- and off-site. These processes differentiate it from the traditional compliance-based snapshot approach (Lund-Thomsen et al., 2014).

Locke et al. (2009) empirically examined improvements in suppliers' working conditions at Honduras Central America when ABC brand cooperated with some of its suppliers for a joint problem-solving exercise. Following the global market shift among apparel brands from Central America to cost competitive options in Asia, ABC informed its Honduras base supplier Sula that it had become less cost-competitive compared to its other suppliers in Asia. But because of Sula's long relationship and attractive location, ABC decided to help in building a new strategy to produce garments in small batches to fulfill rapidly changing consumer demand. The strategy shift did considerably reduce lead time, however, resulting in multiple labor violations. ABC continued to put pressure on Sula for a more cost-effective production planning strategy. As a result, Sula came up with more flexible production shift strategy that reduced efficiency drops from 20 percent to just 4 percent. Consistent pressure and technical assistance from ABC helped Sula improve productivity. This is a classic example of a commitment-based approach to auditing.

Following the success of its commitment-based approach model, ABC used this approach to tackle high turnover rates with its Indian supplier, and health and safety issues with one of its suppliers in the Dominican Republic (Locke et al., 2009; Locke et al., 2013). Frenkel et al. (2002) conducted an empirical study on two Adidas footwear suppliers in China. The suppliers took different approaches to factory audits. One supplier followed a compliance-based model, Beta, while the other followed a commitment-based approach, called Alpha. Frenkel et al. (2002) found that Alpha was able to enforce code more strictly and efficiently than Beta because of differences in the mindsets of the managers. Beta's manager perceived codes as a target, while Alpha's manager treated codes as platform that needed continuous effort and iteration to improve labor practices. Alpha's management was prepared to invest in new factory labor practice

initiatives enforced by Adidas and was more open to collaborating with the Adidas compliance team. This study illustrates the critical insights which favor a commitment-based approach over a compliance-based approach to factory audit.

Though the commitment-based approach places emphasis on upgrading suppliers' factory management processes, critics of this approach question its ability to be executed across the brand's overall supply infrastructure. Although the cooperative inspection does work for a few suppliers (Locke et al., 2009; Locke et al., 2013), it falls short in tracking the entirety of a supplier's overall working conditions, because of the continuous work required by the brand. In today's cost-competitive and lead-time-focused apparel world, it becomes especially apparent that apparel brands usually expect suppliers to handle most of the costs associated with labor issues (Lund-Thomsen et al., 2014; Yu, 2009).

Distelhorst et al. (2016) conducted a study on more than 300 Nike factories across 11 countries, including India, China, Vietnam, Sri Lanka, Malaysia, and Thailand. They found that a commitment-based approach did reduce non-compliance by 15 percent, but these findings were not consistent across all countries. For example, Nike suppliers in China and Sri Lanka did not see a decline in non-compliance even with a commitment-based approach to factory audit, which poses questions about the ability of the collaborative approach to address labor violations across the supply base of any global apparel brand.

Based on a detailed review of both traditional compliance-based, and commitment-based audit models, continuous emphasis from field scholars on a new form of monitoring that can ensure the utilization of local resources, feasible representation of workers in the monitoring process, and the continuous flow of information exchange between suppliers and brands (Bouchery et al., 2016; Brown, 2017; Martin, 2015; Locke et al., 2009; Lund-Thomsen et al.,

2014; O'Rourke, 2000), this dissertation proposes a new data source. This new source, entitled workers feedback crowdsourcing, is based on a workplace feedback system employed by XYZ, a third-party monitoring service provider.

Before getting into the details about the proposed data source and how it differs from current labor information, the phenomenon of "decoupling" needs to be discussed. Depending on various factors, brands may follow compliance practices that do not fully adhere to core business procedures. In existing literature, this phenomenon is known as "decoupling." The tension between compliance and sourcing within brands, and bad sourcing practices (such as frequent changes in order, and bad forecasting) are some of the factors leading to decoupling in supply chain compliance (Locke et al., 2013).

In his case study, Locke et al. (2009) discovered that ABC was working with all its suppliers in Bangladesh even after the disapproval of its compliance team. In one visit, the auditor recalled that the sourcing department had sold samples before the audit started. The auditor knew that ABC would have given the supplier its business regardless of whatever compliance violations were found and reported. According to an executive of ABC (Locke et al, 2009), "pulling out of a factory or an entire region can amount to approximately 20 cents per garment because the average price amounts to only $6.75." (p.335)

This dissertation assumes that there is no decoupling, and that brands are genuinely interested in improving factory working conditions. The following will discuss the differences between the proposed monitoring tool and the social audit.

2.5 A Comparison of Workers Feedback Crowdsourcing and Audits

Traditional audit practices enhance transparency, while other methods emphasize improving workplace visibility. For example, Labor Link (Schwartz., 2013) and XYZ (Lahiri, 2012), two

supply chain technology startups, use crowdsourcing data from workers to report both worker job satisfaction and labor compliance violations at the factory level. Workers feedback Crowdsourcing data is collected using cell phone surveys completed by factory workers via a toll-free number (Newlands, 2017). Factory workers can use this number to anonymously report abuses within the apparel factory. In 2015, XYZ launched Symphony, a new SaaS platform, in the apparel sectors of Bangladesh and Turkey. The details of the differences between workers feedback crowdsourcing and traditional factory audits are listed in Table 2.1.

The three big players in workers feedback crowdsourcing are Labor Links, Labor Voices, and Ulula. Labor Links was the first to use this feedback crowdsourcing ecosystem, started in 2011. Labor Links gathered three million responses from one million workers from sixteen countries to date. Labor Links covers many industries, such as electronics, apparel, and toys. Labor Voices started in 2015 and gathered half million responses from forty thousand apparel industry workers in Bangladesh and Turkey. Ulula started in 2013 and focuses on workers in Africa.

Instead of using a pre-existing crowdsourcing company such as Labor Link or Labor Voices, brands such as Gap and American Eagle have approached feedback crowdsourcing either by building their own data sourcing systems (Sustainability, 2017) or by collaborating with external merchants (Improvement, 2017). In any case, worker participation is critical to labor code compliance and contributes significantly to labor standards improvements (Yu, 2009). In this dissertation, worker crowdsourced data is used as visibility tool, not as a verification tool because of this researcher's inaccessibility to factory audit reports.

Table 2.1

Workers Feedback Crowdsourcing Tools and Factory Audit Comparison

Workers Feedback Crowdsourcing Tools	**Traditional Factory Audits**
Workers complete cell phone surveys that contain prerecorded questions such as. "Did you get paid on time last month?" Yes or No? Workers can also call a toll-free number any time to record any abuse. Worker responses are saved in CSV files.	One to three auditors visit an apparel factory facility for some hours (in some cases a couple of days) and take note of anything not aligned with minimal requirements. Based on these observations, the auditor then submits a corrective action plan to both the supplier and the brand. Finally, there is a follow–up visit to check for improvements within 6 months to 2 years. The time span depends on the supply base and resources of the brand.
Workers Feedback Crowdsourcing is a continuous monitoring approach. Workers provide information on an ongoing basis.	Factory audit is a snapshot approach. Information exchange depends on the number of audits conducted per factory on a yearly basis. The typical apparel industry practice is at least one yearly audit per factory.
Workers Feedback Crowdsourcing is an independent platform that treats everyone, including workers, as users/customers.	Multi-stakeholder initiatives are often biased toward the brand.
Workers are sometimes offered incentives such as free minutes of cell phone talk time.	There is no direct incentive for workers.

Table 2.1 Workers Feedback Crowdsourcing Tools and Factory Audit Comparison (Continued)	
Workers Feedback Crowdsourcing Tools	**Traditional Factory Audits**
Workers Feedback Crowdsourcing is a visibility tool. However, the brand and/or supplier can use this information to develop verification strategies.	Remediation and penalties are often involved, depending on the reputation consciousness of the brand.
There is no auditor in the information line. Information comes directly from factory workers.	The authenticity of information depends on the honesty of the auditor.
Workers can use this system without affecting their productivity.	Workplace inspections are intrusive to the supplier and can disrupt routine operations.
Workers can use this system without the influence of factory management.	Workers may be prepped beforehand to respond positively to on-site reviews.
Technology integration allows this strategy to be easily scalable, irrespective of the size of the firm's supply chain.	Traditional inspections falter when faced with detecting problems in large supply chains. Tracking performance metrics also becomes difficult.

Based on detailed literature on existing audit practices (Locke et al., 2009; Lund-Thomsen et al., 2014), emerging workers feedback crowdsourcing (Bouchery et al., 2016), and various scholars' views on addressing labor disputes by putting workers in the center of monitoring process or by giving workers appropriate representation in the factory management

process (O'Rourke, 2003; Rodríguez-Garavito, 2005; Anner et al., 2013; O'Rourke, 2000), a comprehensive existing monitoring model in the apparel industry is presented. In this model, worker crowdsourcing complements existing audit practices (Franzese et al., 2017), and private monitoring complements existing state regulatory efforts to ensure joint liability in case of any apparel factory accident. Figure 2.2 illustrates this kind of apparel supply chain monitoring model.

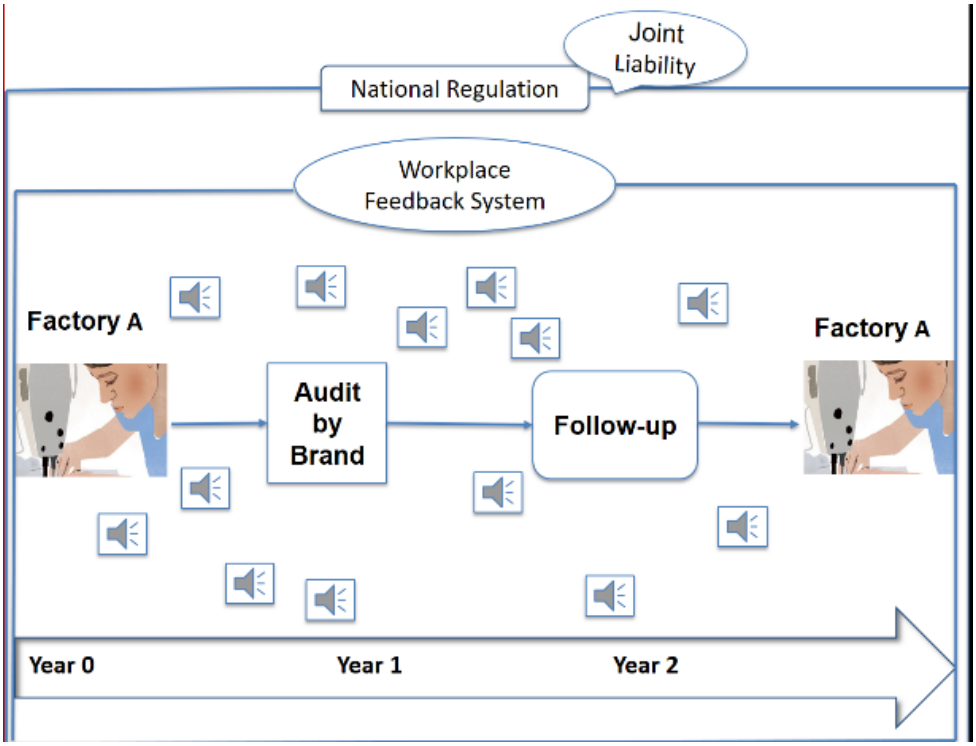


Figure 2.2. A Comprehensive Monitoring Model in Apparel Industry

This model is closest to the monitoring model running in Bangladesh. The government of Bangladesh started a notable initiative called Accord Alliance right after the Rana Plaza collapse (Anner et al., 2013). More than thirty apparel brands, including PVH, H&M, and Zara, signed the Accord along with union federations such as IndustriALL and Union Network International (UNI). According to the Accord, retailers and brands will be jointly liable along with suppliers in case of factory accidents or worker strikes. The joint liability occurs in the forms of financial

compulsion to support suppliers in improving safety precautions and compensating loss of worker hours in the form of salaries (Anner et al., 2013).

2.6 Publicity and News Headlines

For the last couple of decades, the media has played a significant role in maintaining pressure on brands to improve their supplier quality standards by publishing negative headlines that capture the attention of consumers. In reaction, brands have gone to great lengths to document and market their improvement initiatives, typically in CSR reports. As one study found, there was a positive correlation between negative media coverage and improved disclosure of noncompliance in the brands' CSR reports (Islam M. A., 2010).

When there are labor compliance violations, strikes and factory incidents soon follow. Strikes develop because of worker reactions toward any form of abuse within the factory (McAdam et al., 2002). Some strikes may lead to some form of social change (McAdam et al., 2002). Negative media coverage from said strikes may harm the reputation of the brand. For instance, in 2013, a series of disruptive events including building collapses and factory fires in Bangladesh, Pakistan, and Indonesia prompted worker activism and further protests. In theory, factories focused on labor compliance initiatives and treating workers fairly will not bear the true impact of negative publicity. This dissertation will attempt to test this statement.

2.7 Factory Characteristics

Ownership, size, and the supplier's overall relationship with the partner brand are some factory characteristics that may impact labor compliance improvement. For example, large factories can better address labor compliance violations because of their extensive financial resources (Bloom et al., 2012). Similarly, domestic, and government-owned factories may perform poorly because of their limited knowledge regarding international labor regulations, ineffective inspection

protocols, and weaker financial resources (Bloom et al., 2012). The literature supports many factory characteristics that may impact labor compliance. The indicators mentioned here overlap with some of the codes of conduct that are consistent among stakeholders in the apparel industry (see Appendix A).

2.7.1 Certification

Certification, along with codes, are ways to achieve diffusion of global labor standards (Toffel et al., 2015). A certification is a "mode of social regulation" (Bartley, 2007, p. 1) and an indicator of a manufacturer's product quality. Many labor standards certification programs are available through different auditors and other service providers. These certification programs include, for example, SA8000, WRAP, and WRC (Ansary et al., 2015; O'Rourke, 2003). Once a factory is certified, it may be subject to continued inspection, depending on certification continuation criteria.

Certification and codes of conduct are ways to achieve a diffusion of global labor standards (Toffel et al., 2015). They help improve factory management practices to help suppliers adhere to codes of conduct. Empirical studies of certified factories detected the presence of better factory management practices in certified factories compared to non–certified factories (Locke et al., 2013; Vinodkumar et al., 2011). Factories with better factory management practices were found to be less likely to face unrest at factory floor and more likely to avoid negative headlines.

2.7.2 Cooperative Inspection

A cooperative investigation approach usually refers to a strategy adopted by buyers to enhance monitoring by cooperating with rather than threatening the supplier with penalties (Locke et al., 2009). The core idea behind the cooperative inspection is "To engage in the process of root-

cause analysis, joint problem solving, information sharing, and the diffusion of best practices that is in the mutual self-interest of the supplier, the auditors, and the global corporations for which they work" (Locke et al., 2013, p. 321). However, threats can also work to improve labor compliance when a supplier falls short (Short et al., 2016).

Numerous studies have shown that a "cooperative inspection"-based factory audit develops trustworthy relationships between suppliers and buyers, and leads to better labor compliance when compared with the negative approach (Locke et al., 2007; Locke et al., 2009; Locke et al., 2013). Therefore, it is unlikely to witness unrest at a factory where the brand collaborates with the supplier for joint problem-solving to improve worker living condition and to avoid negative publicity. Penalizing suppliers can hinder their motivation to cooperate with auditors (Short, 2010).

Announced auditing is one of the ways to signal cooperation with suppliers. In an announced audit, the buyer tells the supplier about the auditing schedule before conducting the audit. Proponents of announced audits believe that although they may detect fewer violations, they strengthen the buyer-supplier relationship, and may lead to a gradual improvement on the suppliers' part (Short et al., 2016). On the other hand, proponents of unannounced audits, who in most cases are activists, believe that this approach is better at revealing the actual working conditions at the factory.

2.7.3 Buyer-Supplier Relationship

A supplier may turn to subcontractors (Tier 2 or 3) when faced with a short lead time to deliver an order that is beyond their manufacturing or production capability. When suppliers subcontract, they temporarily or permanently send the manufacturing of products to another location or apparel factory they do not own (Van Mieghem, 1999). Subcontracting helps

suppliers reduce cost, since typically a subcontractor manufactures the product at a lower cost. However, an issue arises when suppliers engage in subcontracting without the permission of the brand. If a brand does not know about the subcontractor, the brand will be unable to implement and enforce labor standards. This situation may lead to workplace accidents like the one at Rana Plaza.

Various studies have been conducted to examine how the buyer-supplier relationship can impact labor compliance improvement (Frenkel et al., 2002). Nike implemented a lean manufacturing initiative with its suppliers. Lean manufacturing required collaboration between Nike and the suppliers' factories to successfully enhance productivity. The collaboration was a success, resulting in a 15 percent decline in labor-related noncompliance issues in partner factories (Distelhorst et al., 2016). As seen with Nike, a strategic and influential buyer can exert control over the supplier's practices (Tier 1).

Factors influencing the traditional auditing process include the training level of the auditor, factory characteristics, and the nature of the supplier-buyer relationship (Short et al., 2016). Hindering conditions, which resist the smooth flow of information exchange between suppliers and buyers, include geographic distance, cultural difference (Hernandez, 2014), and the nature of the auditor-supplier relationship, including poor communication (Gomes-Casseres et al., 2006). If the supplier is a tier 1 or tier 2 supplier, the brand will be in frequent contact with suppliers, compared to a tier 3 supplier. The frequent information exchange will help both the brand and its suppliers to identify and address workplace issues together to enhance workplace environment and to prevent negative headlines.

2.7.4 Worker Recommendation

Worker attitude at the factory level is important, as negative attitudes can lead to unproductive performance and can disrupt the day-to-day operations of the apparel factory and create unrest (Jiang et al., 2009). Worker recommendation is a relatively new concept used by many companies to enhance transparency at the factory level (Lahiri, 2012; Newlands, 2017). The idea of worker recommendation is that only satisfied workers will recommend their factory as a place of employment to family members or others. Therefore, recommended factories will be less likely to face any unrest (protest or strikes) because workers are satisfied. Continuous worker recommendation is a crowdsourcing approach to information exchange among workers, suppliers, and buyers, unlike factory audit policing, which acts as a "snapshot" approach.

2.7.5 Worker Voluntary Feedback

Meaningful participation from workers is key to enhancing working conditions and to attaining a sustainable supply chain (Yu, 2009). Many brands strongly encourage suppliers to build systems to encourage worker participation in these systems. Target and Reebok are good examples. Target's CSR report states that it "Expect[s] suppliers to productively engage workers and value them as critical assets to sustainable business success. This engagement includes respecting the rights of workers to freely associate, engage in worker participation groups and submit individual grievances without fear of retaliation" (policies, 2017). Similarly, Reebok requires its manufacturers to train and provide communication platforms to enhance information exchange and to foster collective bargaining (Yu, 2009).

Worker participation is critical to the implementation of labor code compliance and contributes positively to labor standard improvement (Yu, 2009). Management systems to protect workers are more likely to prosper when workers can provide a supplementary layer of

monitoring, information, and advocacy (Anner et al., 2013). Worker voluntary feedback is valuable in assessing potential labor compliance violations. Frequent feedback from workers provides buyers and suppliers information with which to address workplace issues to help prevent negative headlines.

2.7.6 Wages

Delay in wages is one of the most frequently studied issue in the apparel supply chain literature (Absar, 2001; Berik et al., 2010; Islam M. S., 2008). Fatima, a factory helper in one of the readymade garment factory in Bangladesh said: 'I expect to get my wages by the end of the first week of the following month, but I am often disappointed. I am usually paid around the end of the second week or beginning of third week. I get my overtime payment on the third week and sometimes after three to four' (Absar, 2001, p. 11). Similarly, a teenage female garment factory worker from one the garment factory worker said: 'If you ask our contractor regarding our situation, he will say lot of good things—sufficient salary, proper medication, optimum care and so on, but all are just lies. Sometimes, he delays payment and we starve. We cannot say anything in fear of losing our jobs. And if we lose this little job, we have no other alternative avenue to survive' (Islam M. S., 2008, p. 226).

2.7.7 Long Working Hours

Long working hours with no overtime pay is one of the most frequent non-compliance issues brands and suppliers face. This, coupled with low wage, is a common issue in global apparel and footwear manufacturing factories. China witnessed a surge in protests and strikes over withholding overtime hours for workers. Many workers were migrants, and their employers were holding their IDs and travel documents to recoup their investments in sponsoring their visas and transportation (Domoney, 2007).

Interestingly, factory workers do not necessarily see excessive overtime as a violation of their basic rights. Workers are often fine with overtime if they receive their overtime pay on time. Long working hours become a major issue during peak demand seasons, when factories often push employees to work past the usual overtime limit. Workers in Bangladesh typically work 12 hours a day with no leave. According to The Factory Act of 1965, no employee should work more than ten consecutive days without a break. Long working hours significantly affected job satisfaction of the workers of The RMG sector in Bangladesh (Islam et al., 2012).

2.7.8 Abuse

A survey conducted in China in 2013 found that 70 percent of women experienced some form of sexual harassment in the workplace and that 15 percent of those women left their positions soon after the incident (Larson, 2013). Sexual harassment is one of the major reasons behind high turnover rates in apparel and supplier-owned footwear factories in low-cost countries. In many countries, such as China, sexual harassment is usually considered a taboo topic and rarely brought up to supervisors and senior management (Larson, 2013).

Salary and benefits behavior of managers and supervisors, and work and family life are significantly related to job satisfaction (Islam et al., 2016). When the supervisor adequately guides his or her workers, they are encouraged to work harder and better. On the other hand, inadequate supervision may lead to dissatisfied workers and higher turnover rates (Brown et al., 2008).

2.7.9 Fire Safety

Unsafe factory working conditions can put a worker’s life in danger. Unfortunately, this issue has become a major cause for concern in the apparel and garment manufacturing industries. In 2013, a series of fires and building collapses, including the Rana Plaza collapse, occurred

throughout Bangladesh (Anisul Huq et al., 2014). Since then, many efforts have been made to enhance factory safety transparency. The most notable initiative was the founding of the Accord by the government of Bangladesh. The Accord involved all stakeholders and held them accountable for any violations of safe working conditions. According to one study, poor fire management practices such as locked exit doors and the absence of emergency announcements led to the fire incidents in Bangladesh (Wadud et al., 2014). Therefore, factories with good fire management practices (i.e., fire exit accessibility) are more likely to protect themselves from fire accidents.

2.7.10 Child Labor

Suppliers use child labor to reduce overhead cost, but risk negative publicity and potential lawsuits once discovered by external parties (BSR, 2003). Factory-level worker abuse affects children both physically and emotionally. There are many instances of child labor violations in the apparel industry, but the most frequently discussed incident was the manufacturing of soccer balls by children in Pakistan (Gorgemans, 2005). Nike faced the brunt of negative publicity when a U.S.-based magazine featured a Pakistani child worker sewing a Nike soccer ball. Similar cases were reported in Vietnam and Indonesia in the late nineties. In 1993, the NBC reported that child labor was a common practice with one of Walmart's suppliers in Bangladesh. This negative exposure encouraged hostility and criticism toward the famous brand (Bartley et al., 2014).

2.7.11 Sanitation

Sanitation is becoming a standard for labor compliance. For instance, associations like Bangladesh Garment Manufacturers, Exporters Association (BGMEA), Bangladesh Knitwear Manufacturers, and Exporters Association (BKMEA) want apparel factories to ensure the hygiene of their facilities along with other regulations in working conditions (Rahman et al.,

2010). Tiotangco et al. (2012) identified food, water, sanitation, healthcare, transportation, housing and accommodation, and hygiene as important socio-economic factors in the lives of workers. The quality of these factors relates to the job satisfaction of workers.

2.7.12 Freedom of Association (FOA)

Collective bargaining is "a process through which workers come together and send representatives to negotiate over the terms and conditions of their employment" (Wilkinson et al., 2014, p. 227). Collective bargaining is a negotiation process that often takes place among workers, suppliers, and buyers in the apparel industry. Freedom of association includes "The rights of workers to form independent trade unions, bargain collectively and strike" (Anner, 2012, p. 610). FLA (Anner, 2012, p. 627) defines the right to freely associate as "Workers, without distinction whatsoever, shall have the right to establish and to join organizations of their choosing, subject only to the rules of the organization concerned, without previous authorization. The right to freedom of association begins at the time of employment and continues through the course of employment, including eventual termination and is applicable to unemployed and retired workers." The fundamental difference among FOA rights, low wages, and poor working conditions, is the distinct nature of FOA itself. FOA is a right, while other issues are considered standards (Anner, 2012). FOA enables workers to freely join unions and express their issues and concerns with factory management. Therefore, FOA-protected factories are more likely to listen and address worker concerns to ensure better working conditions.

A factory audit is used to detect noncompliance with a brand's code of conduct, but this tool is relatively ineffective in monitoring workers' right to collectively bargain. Anner (2012) conducted a study of FLA audit reports. He found only 5 percent of the FLA violations detected were FOA, compared to 40 percent and 31 percent for safety and low wage-related violations.

This study prompted Anner (2012) to investigate the core reasons behind low FOA violation detection. He concluded that the low rate of FOA violation detection was due to the inadequacy of factory audits.

2.7.13 Forced Overtime

Prohibition of forced overtime is the most consistent criteria set by governing bodies such as ILO, WRAP, and western buyers (O'Rourke, 2003). Forced overtime is most often defined in the context of overtime, as workers are typically not given a choice in setting limits to their working hours. According to China's labor laws, workers can work up to 40 hours per week with optional maximum overtime of 3 hours per day. The company must pay 150 percent of the normal wage for overtime compensation (Yu, 2008). Despite those laws, workers at FS (a Chinese apparel supplier) worked an average of approximately 128 hours per month, exceeding the legal overtime limit. If workers resisted overtime, they were punished with wage reductions (Yu, 2008). Therefore, factories with forced overtime are more likely to face unrest on the factory floor, which may lead to worker protests and strikes.

2.7.14 Clean Water

Clean water accessibility is one of the issues that apparel factory workers face in Bangladesh (Rahman et al., 2010). One study of garment worker conditions in Dhaka & Gazipur found that only 61 percent of workers had access to enough clean water (Farhana et al., 2015). Therefore, lack of clean water accessibility may impact workers' health and lead to dissatisfaction of workers.

2.8 Summary

This literature review reveals that existing factory auditing models are unable to ensure safe and adequate working conditions for factory workers because of poor information generated by

current factory audit processes. Causes of poor information generated from audits include a dependency on unqualified auditors, resource constraints of brands, in-consistent factory audits, and low worker participation. These causes allow a factory audit to inaccurately represent a factory's working conditions. Hence, once poor practices are eventually discovered, apparel brands that employ the services of said factories often see their reputations suffer.

To protect the reputation of apparel brands, as well as to get a true representation of the actual working conditions of apparel factories, this dissertation proposes a new data source, based on actual worker responses. This dissertation is an attempt to empirically examine a workers feedback crowdsourcing data source to answer the main research question: Can we use workers' feedback crowdsourcing to protect apparel factories and brands from reputational damage? by using two research objectives: (1) to determine the association of factory characteristics (i.e., workers grievances and factory indicators) with the negative publicity of apparel factories, and (2) to identify the differences between factories that received negative publicity and those that did not, based on factory characteristics.

CHAPTER 3: METHODOLOGY

This chapter outlines the methodology used in the research. It contains seven sections: (1) conceptual framework, (2) research purpose and objectives, (3) research design, (4) workplace feedback system, (5) survey instrumentation, (6) data collection, and (7) data analysis.

3.1 Conceptual Framework

3.1.1 Transactional Cost Economics (TCE)

Transactional cost economics (TCE) theory concerns the governance of economic transactions (Williamson, 1985). These economic transactions vary based on the nature of the business practices and the way those practices are being managed. TCE helps businesses to determine whether it is cheaper to produce products by building in-house production capability or to outsource production.

TCE supports the logic of mitigating reputational risks by vertically integrating activities that are prone to reputation spillovers to ensure the control of a brand across all its activities (Nickerson et al., 2003; Mayer et al., 2004; Short et al., 2016). However, apparel brands continue to expand the global production network by outsourcing production to low-cost countries to ensure maximum profitability (Mayer et al., 2004; Short et al., 2016). Outsourcing production also outsources production risks which can lead to reputational damage to brands. To control reputational risk, brands are implementing stringent supplier monitoring programs. These programs consist of the codes of conduct audited by the brands. Brands require suppliers to adhere to the codes of conduct; in order to remain in the business suppliers must ensure workplace safety for apparel factory workers (Short et al., 2016). This dissertation tested whether code non-compliance leads to reputation risk.

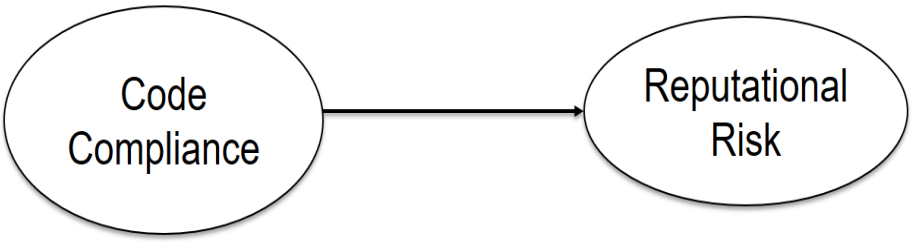


Figure 3.1. Conceptual Framework

Based on the literature, the conceptual framework was constructed for this dissertation. The conceptual framework includes both code compliance and reputational risk. Code compliance is measured by factory characteristics; reputational risk is measured by publicity, found as negative headlines. Factory characteristics are constructed using data from the factory level and the worker level. Factory characteristics based on factory-level data include certification, cooperative inspection, and buyer-supplier relationship. Factory characteristics based on worker-level data include worker recommendations, worker voluntary feedback, wages, long working hours, abuse, fire safety, child labor, toilet sanitation, canteen sanitation, freedom of association, forced overtime, and clean water (see Figure 3.1).

In this dissertation, publicity was operationally defined as the presence or absence of value-based negative publicity (i.e., negative headlines). Negative publicity can be performance- or value-based (Pullig et al., 2006). Performance-based negative publicity arises from events related to product performance (i.e., product failure), while value-based negative publicity occurs because of society-related issues (i.e., labor abuse). Media publicity plays a vital role in protecting or hurting the public reputation of any company (Kim et al., 2007). Negative events generate negative publicity and eventually hurt the brand's reputation among consumers. In this dissertation, publicity was a proxy for adherence to labor standards and labeled labor

compliance. Media from both local Bangladeshi and international English-language newspapers were used to gather factory-specific negative news headlines from 2016.

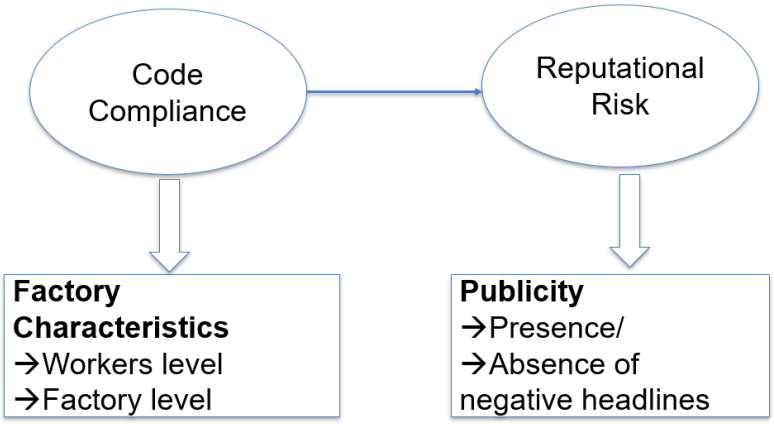


Figure 3.2. Operational Definition of Conceptual Framework

3.2 Research Purpose and Objectives

The following research purposes and objectives defined the goals of this dissertation.

Research Purpose:

The purpose of the dissertation was to conduct the first ever empirical study that used workers feedback crowdsourcing data to answer the research question: Can we use workers' feedback crowdsourcing to protect apparel factories and brands from reputational damage? Two research objectives were investigated to answer the main research question. The first objective was to determine the association of factory characteristics (i.e., workers grievances and factory indicators) with the negative publicity of apparel factories in Bangladesh for the year 2016. The second objective was to identify the differences between factories that received negative publicity and those that did not, based on factory characteristics. The significance of this relationship has important implications. The proposed data source can be used in addition to existing factory audits approaches to gather the most up-to-date information about the factory conditions which may further save brands from negative headlines. By showing which

relationships were significant, this dissertation provides, to my knowledge, the first empirical support for using workers feedback crowdsourcing data for monitoring the working conditions at apparel factories to limit reputational damage. The research question was answered by measuring the two research objectives listed below:

Research Objective 1:

The first objective was to determine the association of factory characteristics (i.e., workers grievances and factory indicators) with the negative publicity of apparel factories.

RO1a: To determine whether the type of publicity is associated with workers voluntarily providing feedback.

RO1b: To determine whether delay in wages are related to negative publicity.

RO1c: To determine whether the fire safety violations are associated with negative publicity.

RO1d: To determine the relationship between the level of sanitation (both for toilet and canteen) and the type of publicity.

RO1e: To determine whether workplace abuse is associated with negative publicity.

RO1f: To determine whether child labor is related to negative publicity.

RO1g: To determine the relationship between worker recommendation and type of publicity.

RO1h: To determine whether the type of publicity is associated with long working hours.

RO1i: To determine whether forced overtime is associated with negative publicity.

RO1j: To determine whether FOA rights violation is associated with negative publicity.

RO1k: To determine whether clean water is associated with the absence of negative publicity.

RO1l: To determine the relationship between the type of brand-supplier relationship and type of publicity.

RO1m: To determine the cooperative inspection approach associated with negative publicity.

RO1n: To determine the certification status associated with negative publicity.

Research Objective 2:

RO2: The second objective was to identify the differences between factories that received negative publicity and those that did not, based on factory characteristics to explore the pattern if any among negative factories.

3.3 Research Design

The purpose of this study was to investigate the relationship between apparel factory working conditions and negative publicity. The first objective of the study was to determine the relationships between 14 different factory characteristics and negative publicity. Due to the exploratory nature of this study and the challenges in obtaining data alternative methods were required. The second objective was to determine the workers issues among the negative factories to determine the triggering factors of negative publicity and to explore the pattern if any across negative factories. A research design was developed that relied on the nature of the data available that would align with the objectives of the study. Surveys were administered to apparel factory workers in Bangladesh using a Workplace Feedback System (WFS) developed by XYZ.

3.3.1 Sample

A non-probability sample of 16,000 factory workers from 194 apparel factories in Bangladesh was used as the basis for the study. Although the number of factories in the sample was small relative to the number of apparel factories in Bangladesh (n=5000+), the focus of this study was on the factories using the WFS (n=350). The unit of analysis for this study was the factory.

3.4 Data Collection

This section is organized into four subsections. The first subsection describes the mechanism for collecting factory worker data, the WFS. The second subsection describes the survey used with

workers that was administered using the WFS. The third section describes the collection of factory level data from public sources. The last section describes the data collection process for evidence of negative publicity. All of the data cover the time period from January 1, 2016 to December 31, 2016 except the data collection for the news articles to gather negative publicity of sample factories which was from January 1, 2016 to January 31, 2017. This time period was selected as the workers feedback data collected throughout 2016. An additional month of January from 2017 was added to capture any negative headline because of the workers grievances from the month of December 2016.

3.4.1 Workplace Feedback System (WFS)

The WFS is a tool for measuring apparel factory working conditions in real time. It was designed and administered by XYZ, a technology start-up firm. Workers use the system to report on factory conditions. Workers can interact with the system using electronic (i.e. mobile phones) and non-electronic means (i.e. flip boards or cards). Currently, mobile phones are the most common way workers interact with the system.

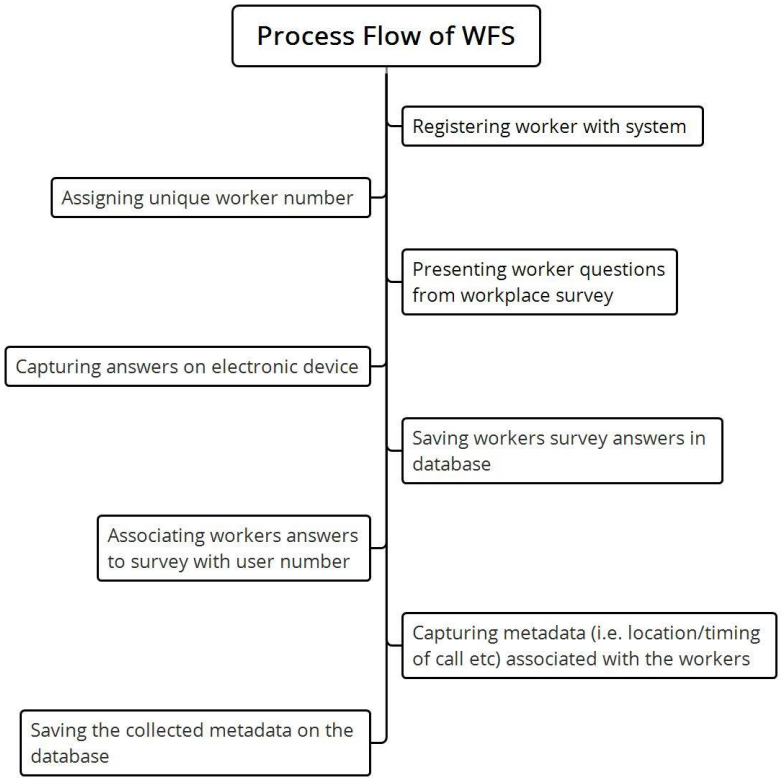


Figure 3.3. Process Flow of Workplace Feedback System

XYZ provides three services using the WFS; collection of data, analysis of data and writing reports using the data. The analysis of data and writing reports using the data are beyond the scope of this study. This study used the WFS for collection of data.

In order for data to be collected, factory workers must register with the system either in-person or by calling a toll-free number. During registration, they provide the WFS with their name, factory name, and mobile phone number. The system creates a record for each factory worker containing 18 columns, corresponding to 18 variables, where data will be stored. The columns of interest in this study were user_id (unique worker identifier), fac_id (unique identifier for the factory), conversation_created_at (timestamp of worker call), page_name (survey question), and user_input (worker response on survey question). Workers are offered incentives to register and use the system. The incentives range from information on topics such

as insurance and healthcare to vocational education and academic scholarships. Brands and the factories pay XYZ for the use of the system.

3.4.2 Factory Worker Survey

The WFS collects data on apparel factory working conditions by administering a survey to workers through electronic or non-electronic means. The survey was written in Bangla. The survey contains 11 items measuring 11 different issues (see Table 3.1).

Table 3.1

Survey Questions

Issue	**Question**	**Answer Choices**
Worker Recommendation	Will you recommend this factory to a friend or family member?	Yes, if will recommend No, if will not recommend
Worker Voluntary Feedback	If you have any other feedback on your factory, press 1 or else press 2.	Yes (if feedback is provided) No (if feedback is not provided)
Wages	In the last month, were all your wages, including overtime hours, paid on time?	Yes, if paid on time No, if not paid on time
Long Hour	In the last month, have you ever worked more than 10 hours in a day?	Yes, if worked more than 10 hours, No, if didn't work more than 10 hours
Abuse	In the last month, have you experienced abuse from a manager, such as swearing, physical abuse, or sexual harassment?	Yes, if experienced No, if not experienced
Fire Safety	Are the fire exits in your factory accessible at all times?	Yes, if always accessible No, if not always accessible

Table 3.1 Survey Questions (Continued)		
Issue	**Question**	**Answer Choices**
Child Labor	In the last month, have you witnessed any child worker in your factory?	Yes, if witnessed No, if not witnessed
Sanitation	On a scale of 0 to 4, how would you rate the cleanliness of the canteen in the last month? On a scale of 0 to 4, how would you rate the cleanliness of the toilet in the last month?	0 = Poor sanitation 1 = Fair 2 = Good 3 = Very good 4 = Excellent sanitation ** Workers were not given any descriptions corresponding to 0 through 4.
FOA	Are you free to join or form trade unions/worker welfare committees in your factory?	Yes, if free to join No, if not free to join
Overtime	Are you forced to work overtime in your factory to avoid non-payment and getting fired?	Yes, if forced No, if not forced
Clean Water	Do you have access to clean drinking water on your factory floor?	Yes, if have access No, if do not have access

XYZ used a structured process to develop the survey. XYZ used apparel brands' Corporate Social Responsibility (CSR) codes and the International Labor Organization (ILO) standards as a basis for writing questions. The initial set of questions were developed by XYZ employees in Dhaka and California. Once the questions were developed, XYZ used a focus group of workers to verify that the questions addressed issues they were facing. Focus group members could suggest additions and deletions to the list of questions. Once the final survey was ready, it was pilot tested with six workers to make sure the questions were understandable and that the workers could use the WFS. Three of the participants had previous experience with WFS

and three did not. Based on the feedback from the six participants, the survey was modified and then retested with the same participants. The survey used in the current study underwent four iterations.

3.4.3 Factory Level Data

Apart from the survey data collected from factory workers, data were collected on the factories using publicly available data. The factory variables are certification, approach to inspection and buyer-supplier relationship. The operational definition for certification is that the company must be listed in the databases of either the Worldwide Responsible Accredited Production (WRAP), SA 8000, or Worker Rights Consortium (WRC). The operational definition of approach to inspection is that either the inspection is announced and paid by the company or not. XYZ provided the classification information. The operational definition of the buyer-supplier relationship is the tier of the supplier. Factories are classified as belonging to supplier tier 1, 2 or 3. The Accord database provided the classification information (see Table 3.2).

3.5 Negative Publicity

The current study defined negative publicity as negative news headlines. The data were collected using Lexis Nexis News Desk (LNND). Lexis Nexis is one of the most comprehensive news data platforms covering a wide range of media sources including both local and international media. In order to use LNND, keywords must be identified. The researcher searched the literature to identify relevant keywords used when investigating factory working condition and labor disputes. Based on the literature, the identified keywords were: sustainability, manufacturing, supply chain, CSR, human rights, labor, Bangladesh, factory, ethics, slave, child labor, human trafficking, wages, Dhaka, safety, death, strikes, dispute, protest, Accord, Alliance, abuse, forced, forced overtime, injuries, pregnant, discrimination, unpaid, Bangladesh factory fire,

suppliers, workers, apparel, garment workers, building collapse, dead, incident, violations, sweatshops, clothing, overtime, poor, working conditions, RMG, disaster, owner, and the name of all factories and the associated brand name. The details of the literature review are listed in Appendix B.

Table 3.2

Factory Level Attributes

Variable	**Description**	**Scoring**
Certification	Factories with safety certification such as WRC, SA8000, and WRAP	1 if factory possess any certification, 0 otherwise
Buyer-Supplier Relationship	This tells if the relationship between buyer and supplier is close. One way to determine this is how frequently they are in contact. This can be answered if the supplier is tier1 and tier 2, or tier3.	1 if the supplier is tier1 or tier2, 0 if the supplier is tier3
Cooperative Inspection	Factories that follow with announced audit inspection or audit inspection paid by brands for joint problem solving, will be referred to as a Cooperative Inspection	1 if factories paid worker responded service provider, 0 otherwise

In addition to keywords, LNND requires several search parameters to be chosen. The *type of data sources* were print and online news articles. The *language of published news articles*

was English. The *country* was Bangladesh. The *industry* was 'Fashion & Apparel' and the *subject* was 'Labor & Employment'. All publicly available news articles from both local Bangladeshi and international news sources meeting these criteria were collected from January 1, 2016 to January 31, 2017. The data were exported from LNND into excel spreadsheets. Three different queries were used to search factory name, group name, and apparel and fashion industry related news in the LNND database. The queries used to search news articles in LNND can be seen in Table 3.3.

Table 3.3

Criteria for Finding News articles

No.	**Query**
1	("Factory Name") AND (contentLocationCountry:Bangladesh OR sourceCountry:Bangladesh)
2	("Group Name") AND (contentLocationCountry:Bangladesh OR sourceCountry:Bangladesh)
3	(Subject: Apparel & Fashion) AND (Industry: Labor & Employment) AND (contentLocationCountry:Bangladesh OR sourceCountry:Bangladesh)

Twenty-four factories were present in the sample with negative headlines. Those factories were referred to as negative factories. The details of the headlines can be seen in appendix C.

3.6 Data Analysis

The data analysis consists of three sections. First, the pre-processing of the data collected is presented. Second, the data analysis to address the first research objective is described. Third, the data analysis for the second research objective is explained.

3.6.1 Data Pre-Processing

3.6.1.1 Factory Worker Survey Data

The data from the survey completed by factory workers using the WFS underwent pre-processing to get it into a form appropriate for analysis. XYZ provided the data to the researcher on 194 separate Excel spreadsheets, one for each factory. The unique factory identifier column, "Fac_ID," was created in each Excel sheet for each of 194 factories. The Excel spreadsheets were imported into Python, where all the sheets were appended into one data set. Irrelevant columns were deleted, and two new columns were created. The first column, "Headlines," was created for recording the presence or absence of negative publicity. The second column, "Version," was created for tracking each version (i.e., updates of the survey questions during the year 2016) of the survey. The python code can be seen in Appendix D.

There were two versions of the survey. Version one contains all the questions listed for datasets 1 and 2 in Table 2 (see Appendix H). Version two contains three questions covering clean water access, forced overtime and freedom of association that replaced sanitation of the canteen, long working hours and worker recommendations. The survey dataset was divided into three, with questions present in both versions as one dataset (i.e., Mod12). The second dataset (Mod12lg) included questions presented in Version '1' covering sanitation of the canteen, long working hours and worker recommendation; the third dataset (i.e., V3) contained three questions presented in Version '2' covering clean water access, forced overtime and freedom of association. The fourth and the only factory-level dataset included buyer-supplier relationship, certification and cooperative inspection. The summary of datasets containing both worker- and factory-level variables included in the final dataset for analysis of the first research objective can be seen in Table 3.4.

Table 3.4

Variables included in the final four datasets

Datasets #	**Level**	**Dataset Name**	**Variables Included**
1	Worker	Mod12	Sanitation of Toilets, Worker Voluntary Feedback, Abuse, Child Labor, Wages, Fire Safety
2	Worker	Mod12lg	Sanitation of Canteen, Long Working Hours, Worker Recommendation
3	Worker	V3	FOA, Clean Water, Forced Overtime
4	Factory	Mod12	Buyer Supplier Relationship, Certification, Cooperative Inspection

There were 1,338 incomplete survey attempts from factory workers in the collected data which were removed from the dataset to avoid an increase in missing responses. This elimination of observations restricted the total maximum survey count to 20,983 workers. The survey counts vary across datasets. Then the missing values were imputed using the median for all survey questions because median is not affected by outliers and is suitable for skewed data (Acuna et al., 2004). The details of the missing count can be seen in Table 3.5.

As can be seen in Table 3.5, the percent of missing data for abuse type dropped to 57.21%. This is because “abuse type” is a nested survey question, meaning that it depends on the answer of the first abuse question which asks workers whether they faced any abuse inside the factory. If first answered as “yes”, then respondents received a question about abuse type. Therefore, the abuse type variable was dropped because of the high proportion of missing values.

Table 3.5

Missing observations count

Factory Worker Survey Data	**Before deleting observations**			**After deleting observations**		
Column	Total	N. Missing	Percentage	Total	N. Missing	Percentage
FOA	7,973	255	3.198	7,973	255	3.198
Forced Overtime	7,973	54	0.677	7,973	54	0.677
Clean Water	7,973	1	0.012	7,973	1	0.012
Worker Recommendation	14,020	1104	7.874	12,980	64	0.493
Long Working Hours	14,020	910	6.497	12,980	9	0.069
Sanitation of Canteen	14,020	1505	10.734	12,980	455	3.51
Worker Voluntary Feedback	22,290	2340	10.497	20,952	1002	4.782
Child Labor	22,290	1938	8.694	20,952	600	2.863
Abuse	22,290	1684	7.554	20,952	346	1.651
Fire Safety	22,290	1560	6.998	20,952	222	1.059
Sanitation of Toilets	22,290	895	4.015	20,952	11	0.052
Wages	22,290	16	0.0717	20,952	16	0.076
Abuse Type	20,606	20311	91.123	20,606	11986	57.21

The three worker-level data sets were analysed for time order discrepancies, based on the 24 factories receiving negative publicity collected through LNND. For example, a negative headline describing factory abuse occurred in April 2016. If there was only one recorded instance of factory-level abuse at that factory, and if it occurred after April 2016, the observation was flagged so as not to be misleading. Eight out of 24 factories receiving negative publicity were removed from the sample because of the absence of worker responses before the headline date. This elimination of factories restricted the total sample size to 186 factories. The factory-

level dataset was not adjusted to the time discrepancies because of the lack of timestamp records for factory-level indicators during the year 2016.

Finally, the worker-level data were aggregated using negative responses from factory workers to form factory-level data. Recall that the unit of analysis in the current study was the factory. The aggregated values were proportions. For example, workers within the same factory responded to the question about child labor ten times during the year. If seven of the ten answers were "yes," the aggregated value for the variable "child labor" was 0.7 for the factory because the "yes" response in this case is negative. The survey contains both "yes" and "no" responses as negative or complaint responses depending on the question. For example, "yes" worker responses for survey questions of worker voluntary feedback, long working hours, abuse, child labor, and forced overtime were grievances while "no" responses for survey questions of worker recommendation, wages, fire safety, FOA, and clean water were grievances. Therefore, worker-level data were aggregated to factory-level based on "yes" responses; then the proportions for variables with "no" responses as grievances were subtracted from one to ensure the consistency of scale for worker complaints (i.e., a proportion close to 1 means worker complaints). Sanitation is the only exception where the average was taken. The proportion of "yes" responses was calculated manually for factories receiving negative publicity. For factories not receiving negative publicity, a Proc Freq procedure in SAS was used. The details of SAS code can be seen in Appendix E. For sanitation related survey responses, the average of responses was done to transform worker level responses to factory level indicator.

For factories that received negative headlines, the worker responses were aggregated within 6 months before the disclosure of negative news article for each factory receiving

negative publicity. The details of the final four datasets used for the analysis of both research objectives can be seen in Table 3.6.

3.6.1.2 Factory-level Data

The missing values in factory data were imputed using the median. There was no transformation needed for the factory-level data as the factory is the unit of analysis for this study. The factories that received negative publicity were separated from those that did not receive negative publicity for all four datasets (three from worker-level data and one from factory-level data) to perform an under-sampling of the majority class.

3.6.2 Data Analysis for Research Objective 1

After gathering and recording the data on the presence or absence of negative headlines for all 194 factories, the data were ready for the analysis. Logistic regression was used to examine the association between the dependent variable "Headline" and the independent variables, which were factory characteristics including both worker-level and factory-level variables. Logistic regression was selected because the response variable headline is binary (1 = negative headline or 0 = absence of negative headline). Linear regression was avoided for the binary response variable because predicted probabilities can exceed the range 0-1, which makes the ultimate results meaningless (Harrell Jr., 2015). The equation for the logistic model is given below.

$$\text{Logit}(p) = \alpha_0 + \sum_{i=1}^{k} \alpha_i x_i \qquad (3.1)$$

where α_0 is the intercept and α_i is the coefficient estimate of the i_{th} of k predictor variables under consideration X1; ...; Xk (Zellner, Keller, & Zellner, 2004).

Table 3.6

Details of the final four datasets used for the analysis of both research objectives

Research Objective	**Analyses**	**Dataset Name**	**Factories with negative headlines**	**Factories with absence of negative headlines**
1	Stepwise Logistic Regression, Exact Logistic Regression, Bootstrap estimate using stepwise logistic regression	Dataset 1: Mod12	16	170
		Dataset 2: Mod12lg	11	109
		Dataset 3: V3	13	127
		Dataset 4: Mod12	16	170
2	Worker response and bar charts	Dataset 1: Mod12	16	170
		Dataset 2: Mod12lg	11	109
		Dataset 3: V3	13	127
		Dataset 4: Mod12	16	170
	Issues frequency analysis, Sentiment Score	Open ended feedbacks	16 factories with 56 worker responses	109 factories with 566 worker responses

The organisation of analysis for both research objectives is given in Figure 3.4. The analysis for the first research question started with the bootstrap sample analysis using stepwise logistic regression to get the factory characteristics that were associated with negative publicity. Then the stepwise logistic regression analysis was done followed by exact logistic regression to see if the findings from bootstrap stepwise logistic regression were consistent with the findings from stepwise logistic regression and exact logistic regression. Any disagreement in the results led to the conclusion that the variable was not significant.

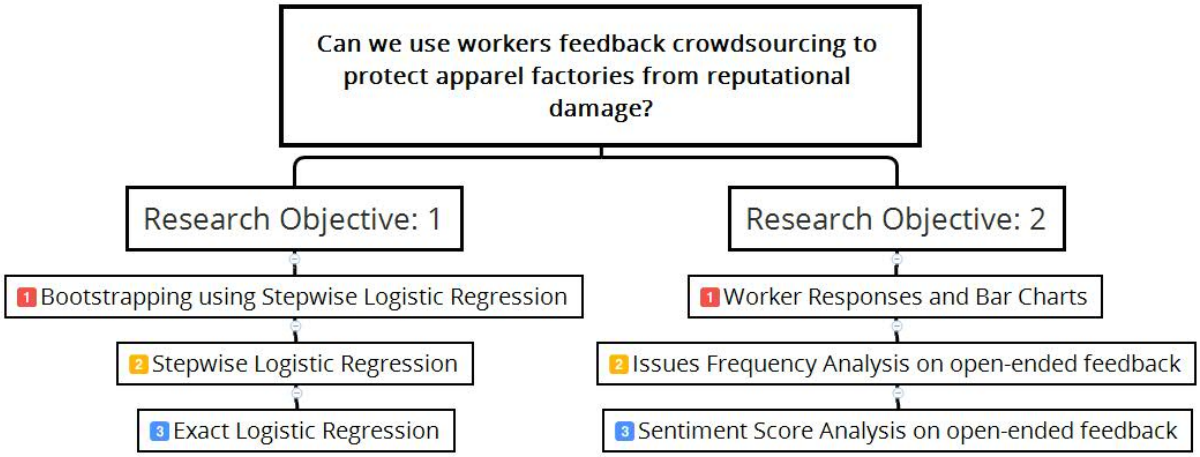


Figure 3.4. The organisation of analysis for both research objectives

To investigate the stability of estimates of predictor variables, the bootstrap method was applied (Chen et al., 1985; Sauerbrei et al., 1992). Efron's bootstrap is a method for obtaining estimates of the properties of statistical estimators without making assumptions about the distribution giving rise to the data (Harrell Jr, 2015; Efron et al., 1986). The basic idea is to repeatedly simulate a sample of specific size, computing the statistic of interest, and assessing how the statistic behaves over certain repetitions (Harrell Jr, 2015).

The bootstrap method was performed using stepwise logistic regression, by creating 1,000 datasets with 16 negative headlines, along with 32 non-negative headlines in each bootstrap dataset. The Base SAS code for bootstrap sampling can be seen in Appendix G.

After applying bootstrap estimates, the Stepwise variable selection process was applied using logistic regression. Stepwise regression is a variable selection process used to pick variables in the model that do not show collinearity among predictor variables (Harrell Jr., 2015). The degree of correlation between the predictor variables affects the rate with which reliable predictor variables find their way into the final model (Derksen et al., 1992). The stepwise variable selection method includes three ways to select important variables: forward, backward, and stepwise selection (Zellner et al., 2004).

In the forward selection, predictor variables were added to a model one at a time. The variable that is included at each step is that which produced the largest reduction in the residual sum of squares. This process continued until all variables were in the model, or until a stopping rule was satisfied. The backward selection starts with all variables included in the model and eliminates variables subsequently one at a time. The variable that is deleted at each step is that which results in the least inflation in the residual sum of squares. This process continued until only one variable was left in the model, or until a stopping rule was satisfied. The stepwise selection is basically a forward selection process; however, at each step the process checks to see whether variables can be dropped from the model using a backward elimination process.

The Akaike's information criterion (AIC) stopping rule was used with a default predictive accuracy (α) of 0.15 (in Base SAS) to perform variable selection using stepwise selection (Harrell Jr., 2015). AIC is a technique for penalizing the log likelihood attained by a given model for its intricacy to get a more impartial assessment of the model's worth. The

penalty is to deduct the number of parameters estimated from the log likelihood, or equivalently to add twice the number of parameters to the −2 log likelihood (Akaike, 1974; Harrell Jr, 2015). The Base SAS code for stepwise logistic regression can be seen in Appendix F.

After applying the stepwise variable selection process, the next step was to perform the exact logistic regression on the output variables of stepwise logistic regression and bootstrap estimate analysis. The exact logistic regression is a simplification of Fisher's exact test, where p-values were calculated by counting all the possible sample outcomes under the null hypothesis (Allison, 2012). The exact method produces valid p-values even in cases of complete or quasi-complete separation and is generally useful when sample sizes are small enough to raise doubts about the accuracy of the chi-square approximation, which is the case for the dataset used in this dissertation. The shortcoming of the exact methods is that they can be very computationally intense (Allison, 2012).

This dissertation's first objective was to investigate the degree of association between factory characteristics and the presence or absence of negative headlines. Exact logistic regression will help determine this degree of association. The Base SAS code for exact logistic regression can be seen in Appendix F.

It was expected that only 10% to 15% of factories in our sample would have negative headlines, which is what we found (i.e., 24 of 194 factories received negative publicity). This scenario may lead to instability of estimates in logistic regression because of the imbalanced class of factories receiving negative publicity. A dataset is imbalanced if the classes are not almost equally represented and the majority class overwhelms the minority class (Kubat et al., 1997). To address the class imbalance and stabilize estimates, original data were re-sampled by under-sampling the majority class (Kubat et al., 1997; Japkowicz, 2000). This was done by

taking twice the number of factories receiving negative publicity than those not receiving negative publicity and repeating until re-sampling covered all factories in the sample. Five subsets were made from each of the four datasets respectively by combining factories receiving negative publicity with those not receiving negative publicity. “Mod121” to “Mod125” represented under-sampled 1 to under-sampled 5 for dataset 1 and dataset 4. “Mod12lg1” to “Mod12lg5” represented under-sampled 1 to under-sampled 5 for dataset 2 respectively. Similarly, “V31” to “V35” represented under-sampled 1 to under-sampled 5 for dataset 3. “Mod12”, “Mod12lg”, and “V3” were the full sampled datasets for the respective datasets. The details of the under-sampled datasets can be seen in Table 3.7. The same under-sampled datasets were used for stepwise logistic and exact logistic regression analysis. For bootstrap estimate analysis, full length sample datasets (i.e., “Mod12”, “Mod12lg”, and “V3”) were used from each of the four datasets.

Four separate regression models were built: three models for each worker-level dataset and one model for the factory-level dataset. Recall that the factory worker survey data was divided into three separate datasets because forced overtime, FOA, and clean water were the questions replacing sanitation of the canteen, long working hours, and recommendation on the second version of the survey. The third dataset contained all questions that were present in both surveys (see Appendix H). The factory-level dataset contained the variables: certification, buyer-supplier relationship, and cooperative inspection. The details of the independent and dependent variables included in each logistic regression model can be seen in Table 3.4.

3.6.3 Data Analysis for Research Objective 2

After identifying the factories with negative headlines, further analyses were done to determine how factories with negative headlines differed from factories that did not have negative

Table 3.7

Sub-sampled Datasets

Dataset #	**Independent Variables**	**Dependent Variable**
Datasets 1: Worker-level responses Mod121, Mod122, Mod123, Mod124, Mod125, Mod12	Abuse, Child Labor, Fire Safety, Wages, Sanitation of Toilets, Worker Voluntary Feedback	Headline
Datasets 2: Worker-level responses Mod12lg1, Mod12lg2, Mod12lg3, Mod12lg4, Mod12lg5, Mod12lg	Sanitation of Canteen, Long Working Hours, Worker Recommendation	Headline
Datasets 3: Version 2 responses V31, V32, V33, V34, V35, V3	FOA, Forced Overtime, Clean Water	Headline
Datasets 4: Factory-level indicators Mod121, Mod122, Mod123, Mod124, Mod125, Mod12	Certification, Cooperative Inspection, Buyer-Supplier Relationship	Headline

headlines. First, graphs were made to detect differences among factories receiving negative publicity. Second, open-ended feedback was collected from workers on the surveys. The open-ended feedback was analysed to better determine the potential cause of a negative headline.

The first step was to make plots of worker responses by placing the worker-response proportion (which is from 0 to 1, with values closer to 1 being more compliant) on the *x-axis* and the type of publicity on the *y-axis* to determine the distribution of worker complaints among factories with negative publicity and those without negative publicity. The second step was to manually analyse the open-ended feedback to determine the most frequent issues faced by workers among factories receiving negative publicity. This helped to understand possible triggers behind a negative headline. The third step was to plot the sentiment score across both negative and those not receiving negative publicity to determine the distribution of factories with negative sentiments. The sentiment score was calculated manually based on the concept of aspect-level sentiment classification where domain knowledge is required and only certain aspects of the document are important to quantify into sentiments (Singh et al., 2013).

The sentiment score was calculated manually, based on 500 workers across 125 factories who provided open-ended feedback. For example, a factory received 10 open-ended statements from workers. Six of these were negative (i.e., complaints) and four were non-negative responses (including both positive and neutral). To calculate the overall sentiment score for the factory, the number of negative statements (-6 in this case) and the number of non-negative statements (4 in this case) were added together (Wan, 2008; Feldman, 2013). If the overall sentiment score result was negative (which is -2 in this case) then the factory was designated as a negative sentiment factory (Wan, 2008; Feldman, 2013). The negative sentiment factory was represented by ‘1’ and

vice versa. This helped to determine whether negative headlines were coming from factories where the overall sentiment was negative and vice versa.

Chapter 4 Data Analysis

This chapter includes data analysis for both research objectives. The first research objective was to determine the association of factory characteristics (i.e., workers grievances and factory indicators) with the negative publicity of apparel factories. Logistic regression with various schemes (i.e., bootstrap estimate, stepwise variable selection, and exact test) was performed to address the first research objective. The purpose of using logistic regression was to determine whether there were any associations between worker complaints about the working conditions inside the factories and negative publicity for apparel factories. The second objective was to identify the differences between factories that received negative publicity and those that did not, based on factory characteristics and to explore the pattern if any across factories receiving negative publicity.

4.1 Association between factory characteristics and negative publicity

The following section presents all the steps of the analysis for the first research objective. It started with the bootstrap estimate distribution analysis using stepwise logistic regression followed by a stepwise logistic regression and concluding with an exact logistic regression analysis.

4.1.1 Bootstrap Estimate Distribution

After first performing the data pre-processing, the data were ready for analysis. The stepwise logistic regression was performed on the bootstrap random samples that contained 1,000 datasets with 16 negative headlines along with almost 32 non-negative headlines in each bootstrap dataset to get the stable estimate and to select the significant variables that were consistent. If the distribution of estimates was skewed on the right side (greater than 0) or left side (less than 0) then that variable was significantly associated with negative publicity.

Table 4.1

Bootstrap estimates distribution using stepwise logistic regression

Dataset #	**Variable**	**Original N**	**N after stepwise**	**Mean**	**Std Dev**	**Min**	**Max**
Dataset 1	Worker Voluntary Feedback	1000	24	-15.51	2.84	-21.22	-11.85
	Wages	1000	5	-6.11	1.12	-7.29	-4.83
	Fire Safety	1000	1	-4.38	.	-4.38	-4.38
	Sanitation of Toilets	1000	652	2.86	0.77	1.62	7.49
	Abuse	1000	0	.	.	.	.
	Child Labor	1000	0	.	.	.	.
Dataset 2	Worker Recommendation	1000	579	-5.4	1.29	-15.6	-3.31
	Long Working Hours	1000	11	9.02	3.55	6.3	19.28
	Sanitation of Canteen	1000	18	1.54	3.56	-5.8	4.59
Dataset 3	Forced Overtime	1000	94	6.52	1.85	4.01	14.7
	FOA	1000	8	3.78	0.4	3.37	4.65
	Clean Water	1000	1	-14.78	.	-14.78	-14.78
Dataset 4	Buyer-Supplier Relationship	1000	76	-2.34	0.03	-2.42	-2.30
	Cooperative Inspection	1000	124	-2.33	0.03	-2.42	-2.30
	Certification	1000	2	-2.22	0.03	-2.24	-2.19

Abuse and Child Labor were not selected by stepwise logistic regression. Sanitation of the canteen was not included because the distribution of estimates included both negative and positive values, as can be seen in Table 4.1. The column “N after stepwise” indicates the number of datasets which selected the respective variable after stepwise logistic regression out of 1000 datasets.

4.1.2 Stepwise Logistic Regression

Next, stepwise logistic regression was applied to each of the original four datasets including the under-sampled subsets to handle any collinearity. The results of the stepwise logistic regression can be seen in Table 4.2.

Table 4.2

Stepwise Logistic Regression

Dataset #		**Variables In**	**Variables Out**
Dataset 1	Mod121	Abuse, Child labor, Fire Safety, Wages, Sanitation of Toilets, Worker Voluntary Feedback	Sanitation of Toilets
	Mod122		Sanitation of Toilets
	Mod123		Sanitation of Toilets
	Mod124		Sanitation of Toilets
	Mod125		No variable selection
	Mod12		Sanitation of Toilets
Dataset 2	Mod12lg1	Sanitation of Canteen, Long Working Hours, Worker Recommendation	No variable selection
	Mod12lg2		Worker Recommendation
	Mod12lg3		Worker Recommendation
	Mod12lg4		Worker Recommendation
	Mod12lg5		No variable selection
	Mod12lg		Worker Recommendation

Table 4.2 Stepwise Logistic Regression (Continued)			
Dataset #		**Variables In**	**Variables Out**
Dataset 3	V31	FOA, Forced Overtime, Clean Water	Forced Overtime
	V32		No variable selection
	V33		No variable selection
	V34		No variable selection
	V35		No variable selection
	V3		Forced Overtime
Dataset 4	Mod121	Certification, Cooperative Inspection, Buyer-Supplier relationship	No variable selection
	Mod122		No variable selection
	Mod123		No variable selection
	Mod124		No variable selection
	Mod125		No variable selection
	Mod12		Cooperative Inspection

The likelihood ratio test (i.e., if $p < 0.05$) for the global null hypothesis of each logistic regression model was checked first; then the significant variables were selected based on the maximum likelihood estimates for each independent variable (i.e., p-value < 0.05). If the p-value for the global null test was less than 0.05, it meant that at least one variable in the model was significant. The detailed outcome of the analysis can be seen in Appendix I.

The parameter estimates and odds ratios of the factory characteristics (sanitation of toilets, worker recommendation, forced overtime, and cooperative inspection) that are associated with negative publicity, based on stepwise logistic regression on all 4 datasets (including subsets)

can be seen in Table 4.3. The sign of the parameter estimates determined if there was a positive or negative association of factory characteristics with the negative publicity of apparel factories. A positive sign of a parameter estimate gave an odds ratio of more than one which implied a positive association and vice versa. In the table below, forced overtime and sanitation of toilets were positively associated with the presence of negative publicity while worker recommendation and cooperative inspection were negatively associated with the presence of negative publicity.

Table 4.3

Parameter estimates from stepwise logistic regression

Dataset #		**Variables**	**Parameter estimates**	**Odds Ratio**
Dataset 2	Mod12, Mod121, Mod122, Mod123, Mod124	Sanitation of Toilets	1.7216, 3.8925, 2.7425, 2.9301, 1.8581	5.593, 48.91, 15.48, 18.72, 6.411
	Mod12lg, Mod12lg2, Mod12lg3, Mod12lg4	Worker Recommendation	-4.0848, -4.5038, -3.5943,-6.4907	0.96, , 0.955, 0.964, 0.937
Dataset 3	V3, V31	Forced Overtime	1.6988, 4.6730	1.01, 1.047
Dataset 4	Mod12	Cooperative Inspection	-1.3122	0.9869

4.1.3 Exact Logistic Regression

The final step was the application of logistic regression with the exact test. The exact test method gives the most accurate result for selecting the important variables. The only downside of the exact test is that it is resource intensive. Sanitation of the canteen, worker recommendation, forced overtime, and cooperative inspection were the only factory characteristics that were significantly associated with negative publicity about apparel factories, based on exact logistic

regression, as can be seen in Table 4.4. Three steps were taken to enter variables in the exact logistic model. First, the output of the stepwise logistic regression was fed into exact logistic regression; then the output of the bootstrap stepwise logistic regression was fed into exact logistic regressionl; and finally the combination of output from both the stepwise logistic regression and the bootstrap stepwise logistic regression were fed into exact logistic regression.The point of the exact logistic regression was to get exact estimates on all possible independent variables to see if the findings from exact logistic regression were consistent with the findings from bootstrap stepwise logistic regression. If no variable was selected after applying the three steps, then the output of stepwise logistic regression was inputted to exact logistic regression (i.e., Dataset1 in Table 4.4). Table 4.4 contains the best possible combinations that output exact estimates.

The parameter estimates and odds ratios of the factory characteristics of sanitation of the canteen, worker recommendation, forced overtime and cooperative inspection are associated with negative publicity, based on exact logistic regression as can be seen in Table 4.5. The sign of the parameter estimates determined if there is a positive or negative association of factory characteristics with the negative publicity of apparel factories. Positive parameter estimates gave an odds ratio of more than one which implied a positive association and vice versa. In the table below, forced overtime and sanitation of canteen were positively associated with the presence of negative publicity while worker recommendation, buyer-supplier relationship and cooperative inspection were negatively associated with the presence of negative publicity. Certification and clean water were not significant because the score test p-values were greater than 0.05.

Table 4.4

Exact Logistic Regression

Dataset #		**Variables In**	**Variables Out**
Dataset 1	Mod121	Sanitation of Toilets	*Error: Not sufficient Memory
	Mod122	Sanitation of Toilets	*Error: Not sufficient Memory
	Mod123	Sanitation of Toilets	*Error: Not sufficient Memory
	Mod124	Sanitation of Toilets	*Error: Not sufficient Memory
	Mod125	No variable selection	No variable selection
	Mod12	Sanitation of Toilets	*Error: Not sufficient Memory
Dataset 2	Mod12lg1	Sanitation of Canteen	Sanitation of Canteen
	Mod12lg2	Worker Recommendation	Worker Recommendation
	Mod12lg3	Worker Recommendation	Worker Recommendation
	Mod12lg4	Worker Recommendation	*Error: Not sufficient Memory
	Mod12lg5	No variable selection	No variable selection
	Mod12lg	Worker Recommendation	Worker Recommendation
Dataset 3	V31	Forced Overtime	Forced Overtime
	V32	Forced Overtime, Clean Water	Forced Overtime
	V33	Forced Overtime	*Error: Not sufficient Memory
	V34	No variable selection	No variable selection
	V35	Forced Overtime	No information because of insignificant global null hypothesis test p-value (i.e., p-value >0.05 see appendix I)

Table 4.4 Exact Logistic Regression (Continued)			
Dataset #		**Variables In**	**Variables Out**
Dataset 3	V3	Forced Overtime	Forced Overtime
Dataset 4	Mod121	Certification, Cooperative Inspection	Cooperative Inspection
	Mod122	Cooperative Inspection, Buyer-Supplier Relationship	Cooperative Inspection, Buyer-Supplier Relationship
	Mod123	Cooperative Inspection, Certification	Cooperative Inspection
	Mod124	No variable selection	No variable selection
	Mod125	Certification, Buyer-Supplier Relationship	No information because of insignificant global null hypothesis test p-value (i.e., p-value >0.05 see appendix I)
	Mod12	Cooperative Inspection, Certification	Cooperative Inspection

*this means that system did not have enough resources to compute the exact estimates

To summarize, the factory characteristics that showed some association (either positive or negative) with negative publicity, based on at least one of the statistical techniques (i.e., stepwise logistic regression on bootstrap sampling, exact logistic regression and stepwise logistic regression) without contradictory findings were worker voluntary feedback, wages, fire safety, sanitation of toilets, long working hours, worker recommendation, FOA, forced overtime, buyer-supplier relationship and cooperative inspection. These findings can be seen in Table 4.6.

Table 4.5

Parameter estimates from exact logistic regression

Dataset #		**Variables**	**Exact Conditional Test Score Test P - Value**	**Exact Parameter estimates**	**Odds Ratio**
2	Mod12lg1, Mod12lg	Sanitation of Canteen	0.0375, 0.0375	2.4402, 2.4402	11.47, 11.47
	Mod12lg Mod12lg2, Mod12lg3	Worker Recommendation	0.0380, 0.0173, 0.0305	-4.127, -4.3603, -3.4768	0.959, 0.957, 0.966
3	V3, V31, V32	Forced Overtime	0.0056, 0.0056, 0.0286	4.5301, 4.5301, 15.4397,	1.046, 1.046, 1.166
	V32	Clean Water	0.0769	Not applicable	Not applicable
4	Mod12, Mod121, Mod122, Mod123	Cooperative Inspection	0.0480, 0.0394, 0.0124, 0.0406	-1.3559, -2.2195, -2.5489, -2.1955	0.257, 0.108, 0.078, 0.111
	Mod122	Buyer-Supplier Relationship	0.0489	-2.33	0.0972
	Mod 12, Mod121, Mod123	Certification	0.1076, 0.1923, 0.2	Not applicable	Not applicable

Abuse and child labor failed to show any association with negative publicity. Sanitation of canteen, clean water and certification showed contradictory findings among logistic models, so they were not significantly associated as well with negative publicity. Sanitation of toilets showed positive association between satisfactory responses with the negative publicity which means there was no association between poor sanitation of toilets and negative publicity.

Table 4.6

Summary of logistic regression analysis

Variables	**Dataset**	**Bootstrap**	**Stepwise logistic Regression**	**Exact**	**Comment**
Worker Voluntary Feedback	1	Negative estimate	No variable selection	No variable selection	No contradiction
Wages	1	Negative estimate	No variable selection	No variable selection	No contradiction
Fire Safety	1	Negative estimate	No variable selection	No variable selection	No contradiction
Sanitation of Toilets	1	Positive estimate	Positive estimate	Unable to calculate because of not enough memory	No contradiction
Abuse	1	Lack of significance	No variable selection	No variable selection	Lack of significance
Child Labor	1	Lack of significance	No variable selection	No variable selection	Lack of significance
Worker Recommendation	2	Negative estimate	Negative estimate	Negative estimate	Consistent
Long Working Hours	2	Positive estimate	No variable selection	No variable selection	No contradiction
Sanitation of Canteen	2	Lack of significance	No variable selection	Positive estimate	Contradiction
Forced Overtime	3	Positive estimate	Positive estimate	Positive estimate	Consistent
FOA	3	Positive estimate	No variable selection	No variable selection	No contradiction
Clean Water	3	Negative estimate	No variable selection	Not significant	Contradiction
Buyer-Supplier Relationship	4	Negative estimate	No variable selection	Negative estimate	Consistent
Cooperative Inspection	4	Negative estimate	Negative estimate	Negative estimate	Consistent
Certification	4	Negative estimate	No variable selection	Not significant	Contradiction

In the next section, all the above-mentioned factory characteristics will be discussed individually including detailed interpretation for research objective 1.

4.2 Interpretation for research objective 1 analysis

4.2.1 Forced Overtime

Forced overtime was the complaint from apparel factory workers that was consistent across all three analyses. The estimated distribution of forced overtime from bootstrap sampling using stepwise logistic regression was greater than 0 (ranges from 4.01 to 14.7), as can be seen in Figure 4.1. The *x-axis* of the bar chart represents the range of the estimates from the bootstrap sampling using logistic regression. The *y-axis* represents the percentage of the frequency of sample factories. The red line indicates the mean of the estimates. This description of the x-axis and y-axis is consistent across all bootstrap distribution charts in this section. An estimate greater than 0 gives an odds ratio of greater than 1, which is a statistical confirmation that there was a positive association.

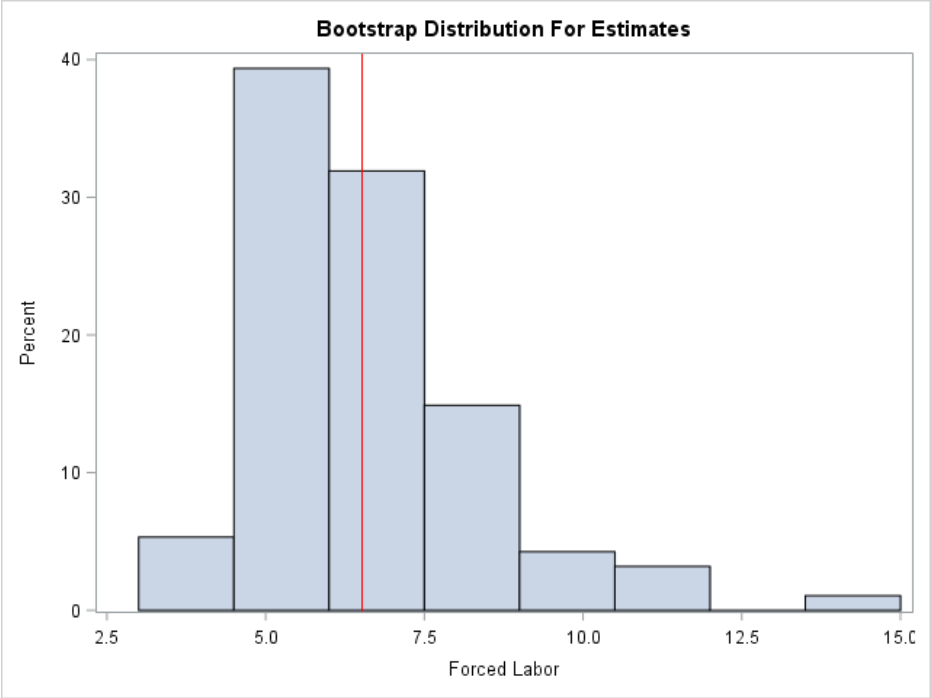


Figure 4.1. Bootstrap estimated distribution of forced overtime

The finding of the bootstrap estimated distribution was also backed by the outcome of the exact logistic regression, which can be seen in Table 4.5. The exact outcome shown in Table 4.7 was from the full dataset V3 as the findings were consistent across subsets V31 and V32.

Table 4.7

Exact logistic regression for forced overtime

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Forced Overtime	Score	5.2870	0.0056	0.0056
	Probability	1.477E-9	0.3786	0.3786

Exact Parameter Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value	Odds Ratio
Forced Overtime	4.5301	2.2663	0.7132	9.3889	0.0111	1.046

In the exact conditional test table, there are two tests: Score test and Probability test. The Score test is favoured over the probability test as it is more robust to skewness in the distribution of the sufficient statistics (i.e., the sufficient statistics are the sums of cross products for each independent variable and the binary dependent variable) (Allison 2012). So, the Exact score p-value will be used from the exact conditional test to see the significance of the independent variables for all exact logistic regressions in this dissertation. The p-value and odds ratio reported in the exact parameter estimate table are constructed on the likelihood ratio tests. The calculation

uses the exact distributions of these statistics instead of the typical chi-square approximation (Allison, 2012).

As can be seen in the table above, the exact conditional test p-value (i.e., 0.0056) of forced overtime indicates it is significantly (i.e., 0.0056< 0.05) associated with negative publicity about apparel factories. The estimate 4.5301 from the table above was divided by 100 and then an exponentiation was taken to calculate a reasonable odds ratio and to avoid an extraordinarily large odds ratio due to difference in scale of worker responses (i.e., 0 to 1) and dependent variables (i.e., 1 or 0). Therefore, the finding from exact logistic regression states that:

For a unit increase in worker complaints (i.e., at level between 1 and 100) of forced overtime in an apparel factory, the odds of getting negative headlines are 1.046 times higher.

These findings of the parameter estimate, and odds ratio were also backed by exact logistic and stepwise logistic regression (see Table 4.3 and 4.5), which provides evidence that forced overtime can lead to negative publicity.

4.2.2 Cooperative Inspection

The cooperative approach to inspection (i.e., announced factory inspection) is the factory-level indicator that was consistent across all three analyses in terms of statistical significance. The estimated distribution of cooperative inspection from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -2.42 to -2.3), as can be seen in Figure 4.2. An estimate less than 0 gives an odds ratio of less than 1, which is a statistical confirmation that there was a negative association.

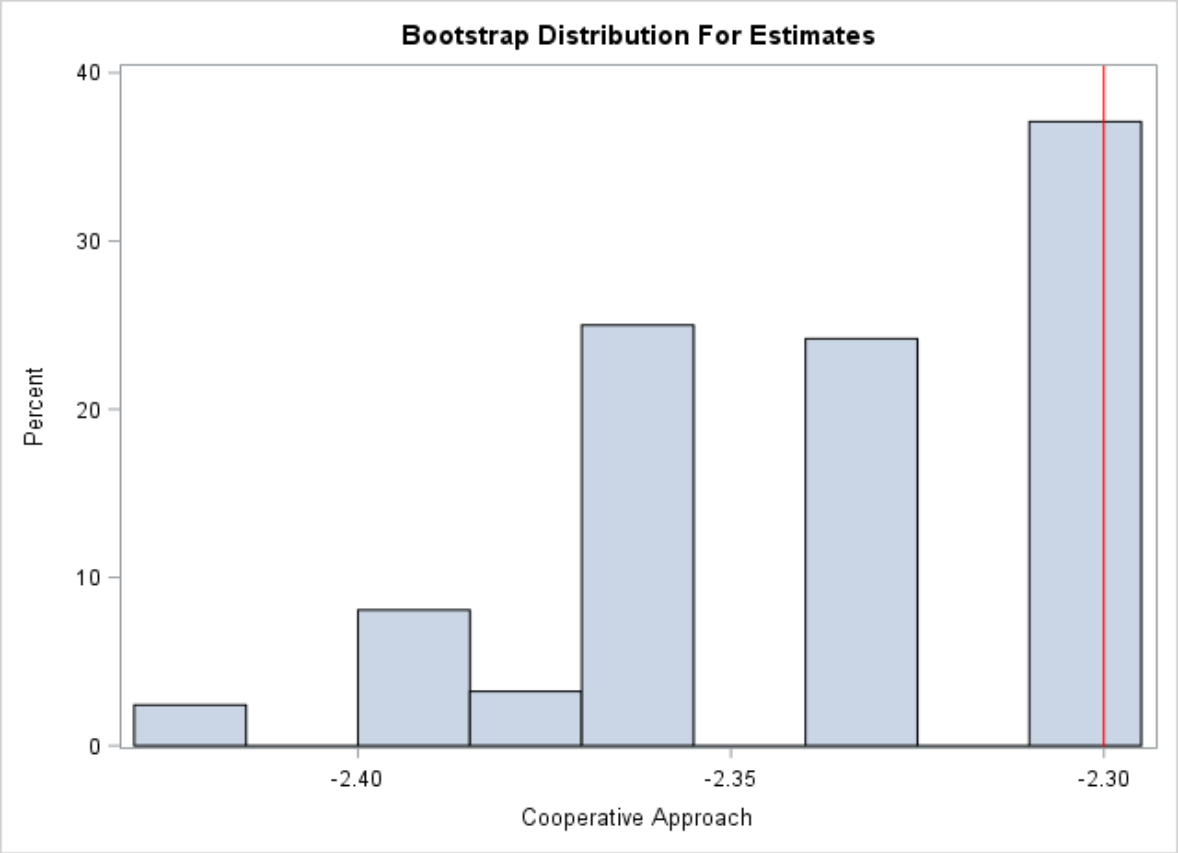


Figure 4.2. Bootstrap estimated distribution of cooperative inspection

The finding of the bootstrap estimated distribution was also backed by the outcome of exact logistic regression, which can be seen in Table 4.5. The exact outcome shown in Table 4.8 was from the full dataset Mod12 as the findings were consistent across the subsampled datasets Mod121, Mod122 and Mod123.

As can be seen in Table 4.8, the exact conditional test p-value (i.e., 0.048) of cooperative inspection indicates that cooperative inspection is significant (i.e., 0.048< 0.05). The finding from the exact logistic regression states that:

For a unit increase in cooperative approach to feedback crowdsourcing in an apparel factory, the odds of not getting negative headlines are 3.88 times higher. This finding suggests a strong association between the cooperative approach and the absence of negative headlines.

Table 4.8

Exact logistic regression for cooperative inspection

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Certification	Score	1.9606	0.2006	0.1439
	Probability	0.1135	0.3121	0.2553
Cooperative Inspection	Score	4.9990	0.0480	0.0285
	Probability	0.0389	0.0480	0.0285

Exact Parameter Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		p-Value	Odds Ratio
Certification	-1.3748	1.0537	-5.1581	0.5794	0.2786	
Cooperative Inspection	-1.3559	0.6456	-2.7509	0.2306	0.0959	0.2577 (flipped 3.88)

These findings from based on the parameter estimates and odds ratio were also backed by the results of the exact logistic and stepwise logistic regressions (see Table 4.3 and 4.5), which provides evidence that the cooperative approach to inspection can lead to a decrease in negative publicity.

4.2.3 Worker Recommendation

Worker recommendation (i.e., announced factory inspection) is the worker-level indicator that was consistent across all three analyses. The estimated distribution of worker recommendation from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -15.6 to -3.31), as can be seen in Figure 4.3. An estimate less than 0 gives an odds ratio of less than 1, which provides evidence that there is a negative association between worker recommendation and negative publicity.

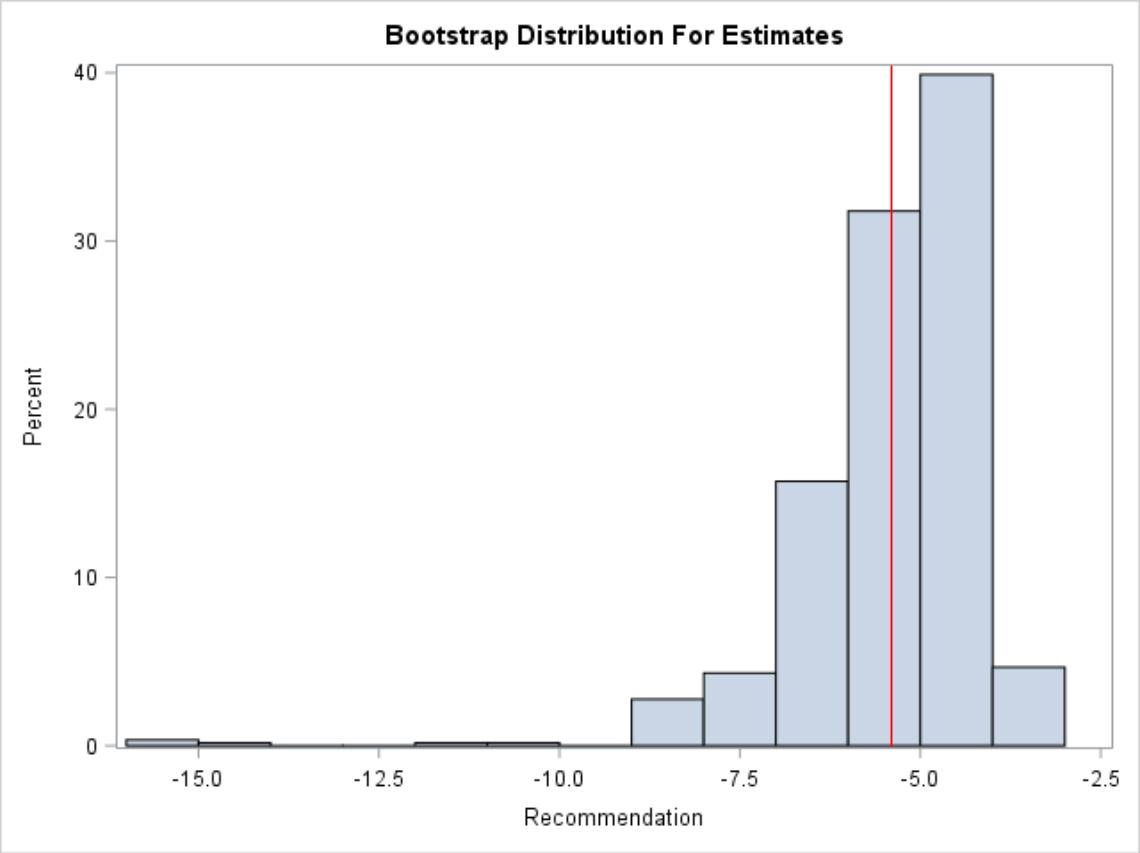


Figure 4.3. Bootstrap estimated distribution of worker recommendation

Similarly, the outcome of the exact logistic regression showed a negative association between no worker recommendation and negative publicity, as can be seen in Table 4.9. The exact outcome shown in Table 4.9 was from the full dataset Mod12lg as the findings were consistent across subsets Mod12lg2 and Mod12lg3.

As can be seen in the table above, the exact conditional test p-value (p-value=0.038) indicates worker recommendation is significantly associated with negative publicity about apparel factories. The estimate from the table above was divided by 100, and then an exponent was taken to calculate a reasonable odds ratio and to avoid an extraordinarily large odds ratio due to a difference in scale of the worker responses (i.e., 0 to 1) and the dependent variables (i.e., 1 or 0). Therefore, the finding from exact logistic regression states:

For a unit increase in no worker recommendation (i.e., at level between 1 and 100) for an apparel factory, the odds of not getting negative headlines are 1.0427 times higher.

These findings from the parameter estimate, and odds ratio agreed with the exact logistic and stepwise logistic regression results (see Table 4.3 and 4.5). Therefore, we confidently conclude that there is evidence for a negative association between no worker recommendation and negative publicity.

Table 4.9

Exact logistic regression for worker recommendation

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Worker Recommendation	Score	4.2199	0.0380	0.0380
	Probability	5.167E-9	0.9982	0.9982

Exact Parameter Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value	Odds ratio
Worker Recommendation	-4.1271	2.1293	-8.7034	-0.2759	0.0340	0.959 or flip 1.0427

4.2.4 Sanitation of the canteen

The estimated distribution of sanitation of the canteen from bootstrap sampling using stepwise logistic regression contains 0 (ranges from -5.8 to 4.59), as can be seen in Figure 4.4. An estimate range that contains 0 means that the finding was not trustworthy; an estimate can occur as negative or positive and eventually can give an odds ratio that may or may not be greater than 0. Therefore, stepwise logistic regression on bootstrap sampling failed to give any statistical

evidence for the significance of the poor sanitation condition of the canteen with negative publicity.

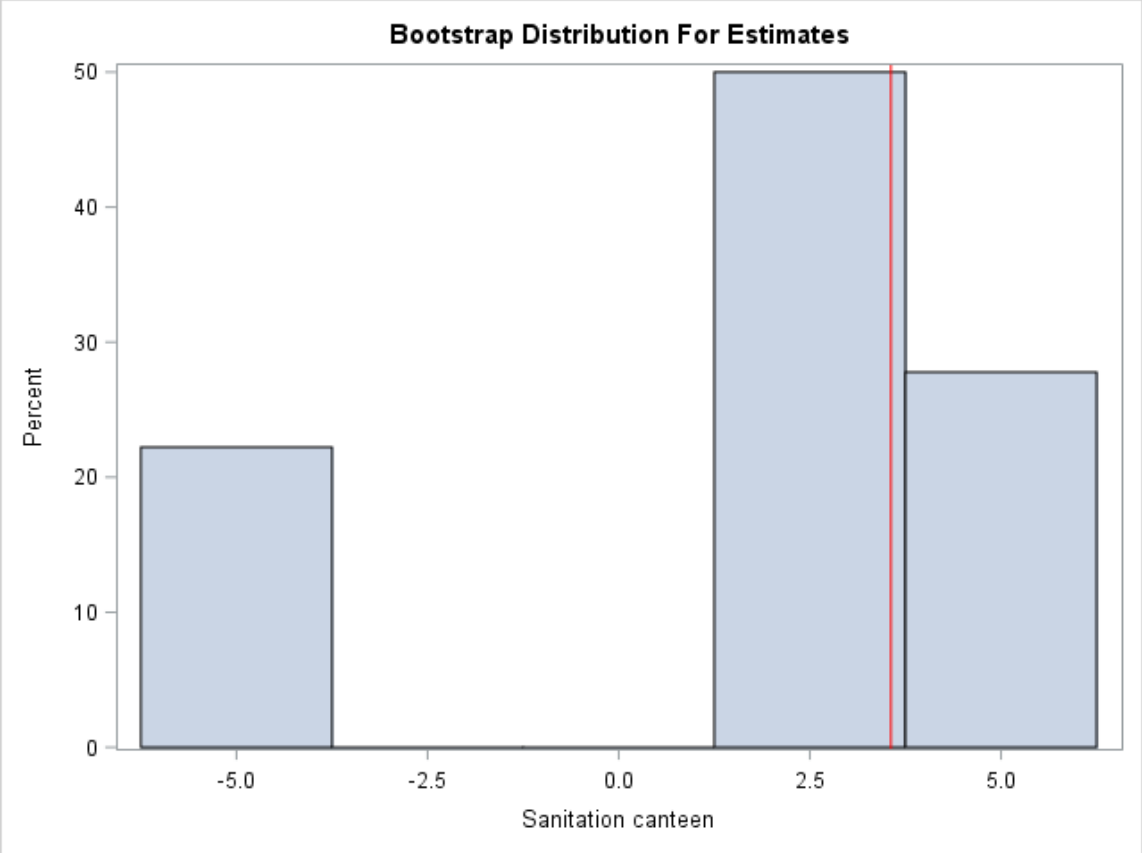


Figure 4.4. Bootstrap estimated distribution of sanitation of the canteen

In contrast, the exact logistic regression results show a positive association between poor sanitation conditions in the canteen with negative publicity, as can be seen in Table 4.10. The exact outcome shown in Table 4.10 was from the full dataset Mod12lg and subset Mod12lg1 as both produced the same results.

As can be seen in the table above, the exact conditional test p-value (i.e., 0.0375) indicates sanitation of the canteen is associated with negative publicity about apparel factories. Therefore, the finding from the exact logistic regression states:

For a unit increase in good sanitation condition for an apparel factory, the odds of getting negative headlines are 11.47 times higher.

Table 4.10

Exact logistic regression for sanitation of the canteen

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Sanitation of canteen	Score	4.2302	0.0375	0.0375
	Probability	5.167E-9	0.9993	0.9993

Exact Parameter Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value	Odds ratio
Sanitation of canteen	2.4402	1.3037	0.1657	5.3528	0.0331	11.47

These findings from the parameter estimate, and odds ratio agreed with the exact logistic and stepwise logistic regression results of under sampled datasets (see Table 4.5), but contradictory to the findings of the bootstrap estimated distribution. Therefore, we cannot conclude that there is no evidence of an association between poor sanitation conditions of canteen and negative publicity.

4.2.5 Worker Voluntary Feedback

The estimated distribution of worker voluntary feedback from bootstrap sampling using logistic regression was less than 0 (ranges from -21.22 to -11.85), as can be seen in Figure 4.5. An estimate less than 0 gives an odds ratio of less than 1, which is a statistical confirmation that there is a negative association between worker voluntary feedback and negative publicity.

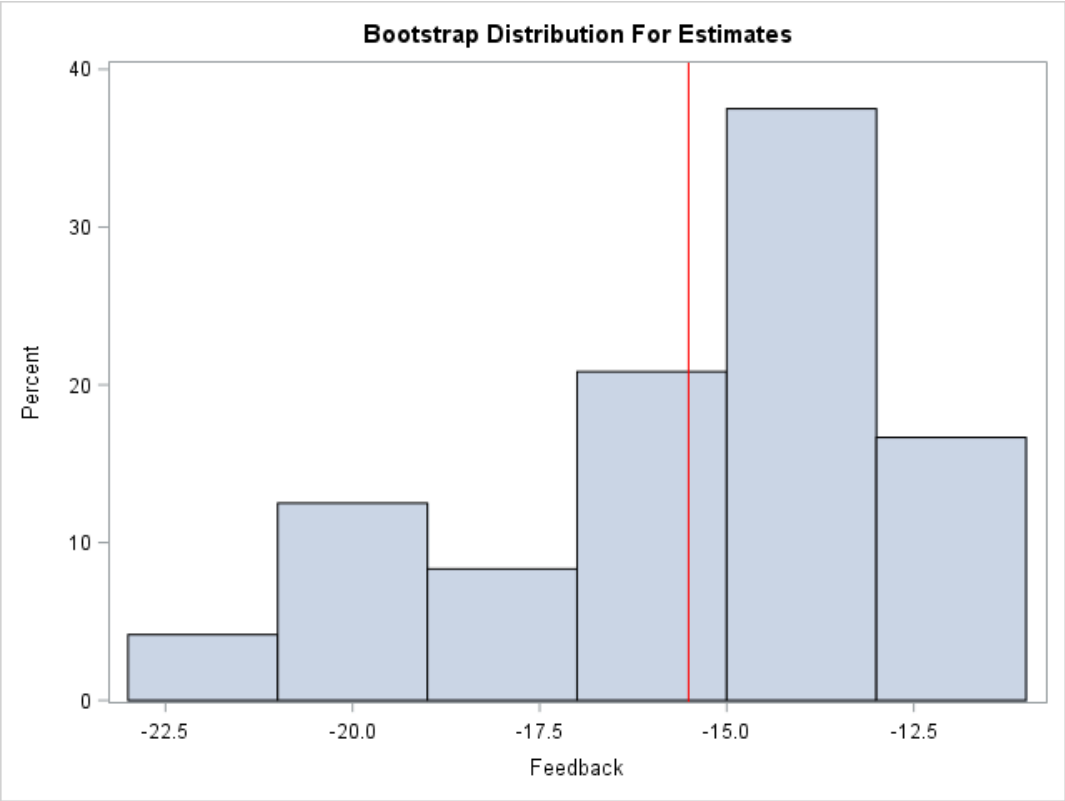


Figure 4.5. Bootstrap estimated distribution of worker voluntary feedback

Worker voluntary feedback was not selected in the exact logistic regression so there is no description of the exact regression analysis presented here.

4.2.6 Sanitation of toilets

The estimated distribution of sanitation of toilets from bootstrap sampling using stepwise logistic regression was greater than 0 (ranges from 1.62 to 7.49), as can be seen in Figure 4.6. An estimate greater than 0 gives an odds ratio of more than 1, which indicates there is a positive association between good sanitation conditions of toilets and negative publicity.

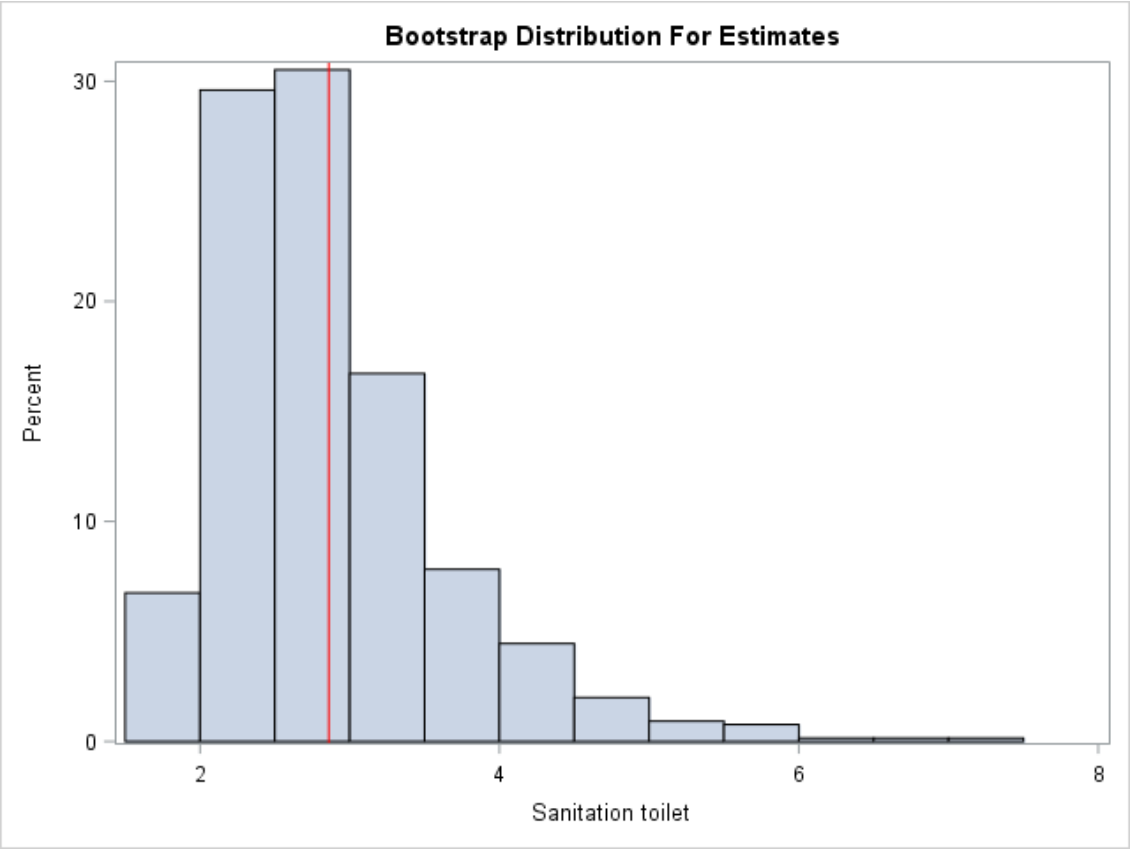


Figure 4.6. Bootstrap estimated distribution of sanitation of toilets

Similarly, the outcome of stepwise logistic regression showed a positive association between good sanitation conditions in toilets and negative publicity, as can be seen in Table 4.11.

Table 4.11

Stepwise Logistic regression for sanitation of toilets

Analysis of Maximum Likelihood Estimates						
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio
Intercept	1	-7.2901	2.1058	11.9852	0.0005	
Sanitation of toilets	1	1.7216	0.7048	5.9671	0.0146	5.59

As can be seen in the table above, the p-value (i.e., 0.0146) indicates sanitation of toilets is associated with negative publicity about apparel factories. Therefore, the finding from stepwise logistic regression states:

For a unit increase in good sanitation conditions of toilets for an apparel factory, the odds of getting negative headlines are 5.59 times higher. This finding suggests a lack of evidence of an association between poor sanitation conditions surrounding toilets and negative Publicity.

These parameter estimate, and odds ratio results agreed with the results of the stepwise logistic regression of under-sampled subsets (see Table 4.3). Therefore, we can confidently conclude that the statistical analysis did not provide any evidence about the association between poor sanitation conditions of the toilets and negative publicity.

4.2.7 Wages

The estimated distribution of wages from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -7.29 to -4.83), as can be seen in Figure 4.7. An estimate less than 0 gives an odds ratio of less than 1, which indicates there is a negative association between delay in wages and negative publicity.

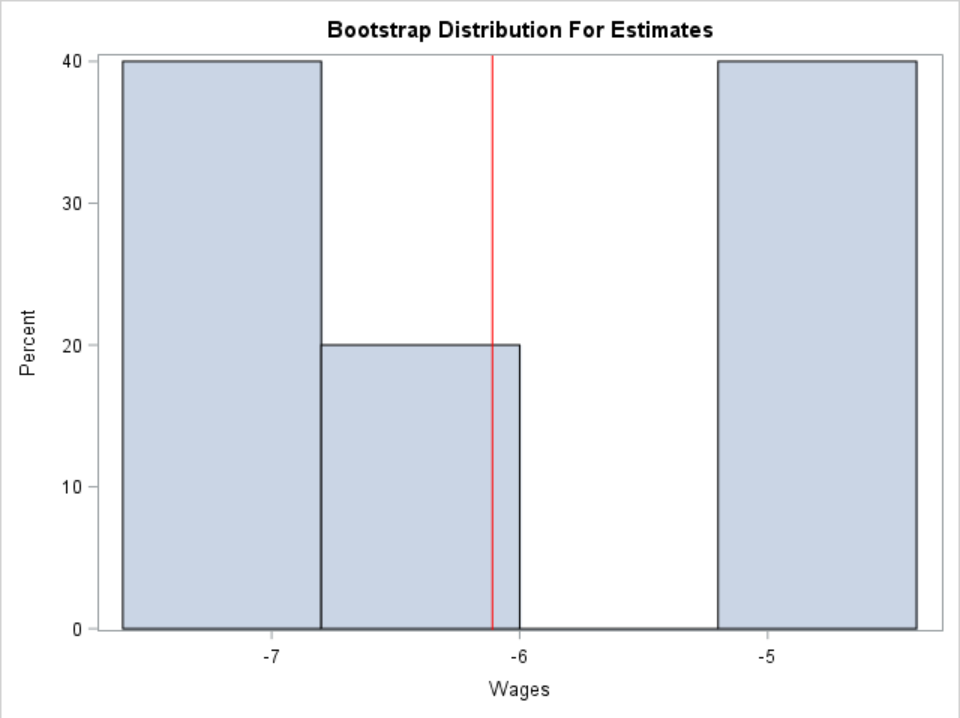


Figure 4.7. Bootstrap estimated distribution of wages

Wages was not selected by exact logistic regression so there is no description of results from the exact regression analysis presented here.

4.2.8 Fire Safety

The estimated distribution of fire safety from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -4.38 to -4.38), as can be seen in Figure 4.8. An estimate less than 0 gives an odds ratio of less than 1, which indicates that there is a negative association between fire safety issues and negative publicity.

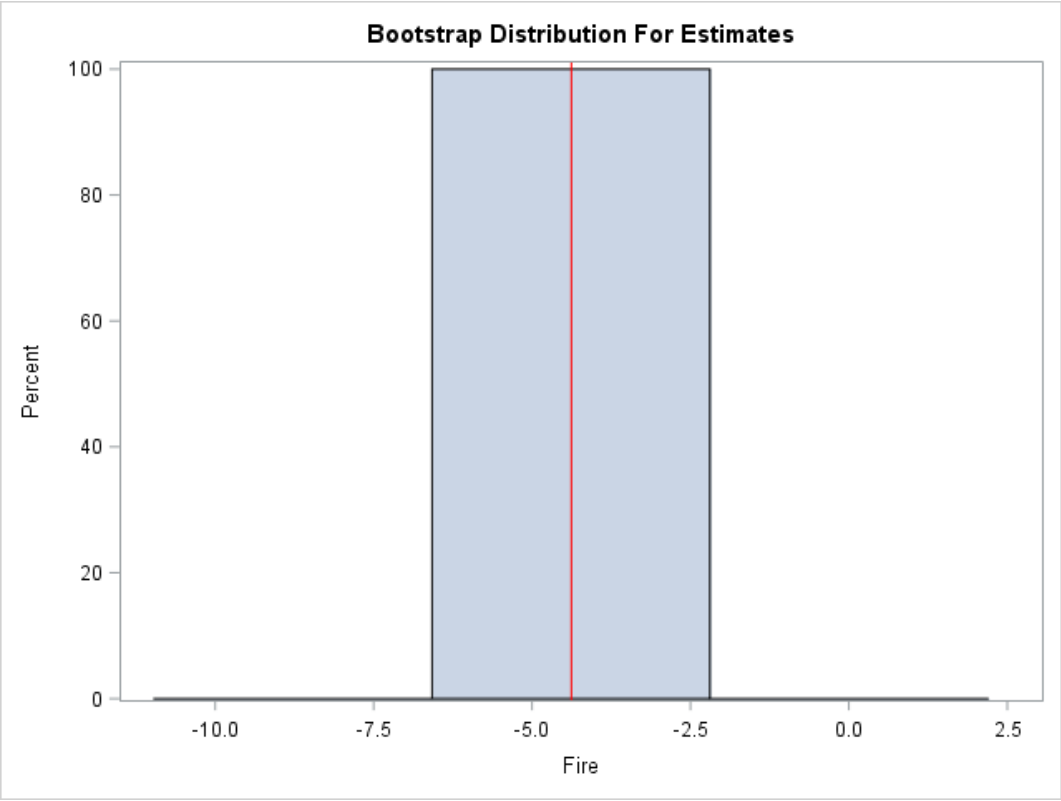


Figure 4.8. Bootstrap estimated distribution of fire safety

Fire safety was not selected by exact logistic regression so there is no description of the results from the exact regression analysis presented here.

4.2.9 Long Working Hours

The estimated distribution of long working hours from bootstrap sampling using stepwise logistic regression was greater than 0 (ranges from 6.3 to 19.28), as can be seen in Figure 4.9. An estimate greater than 0 gives an odds ratio of greater than 1, which indicates that there is a positive association between long working hours complaints and negative publicity.

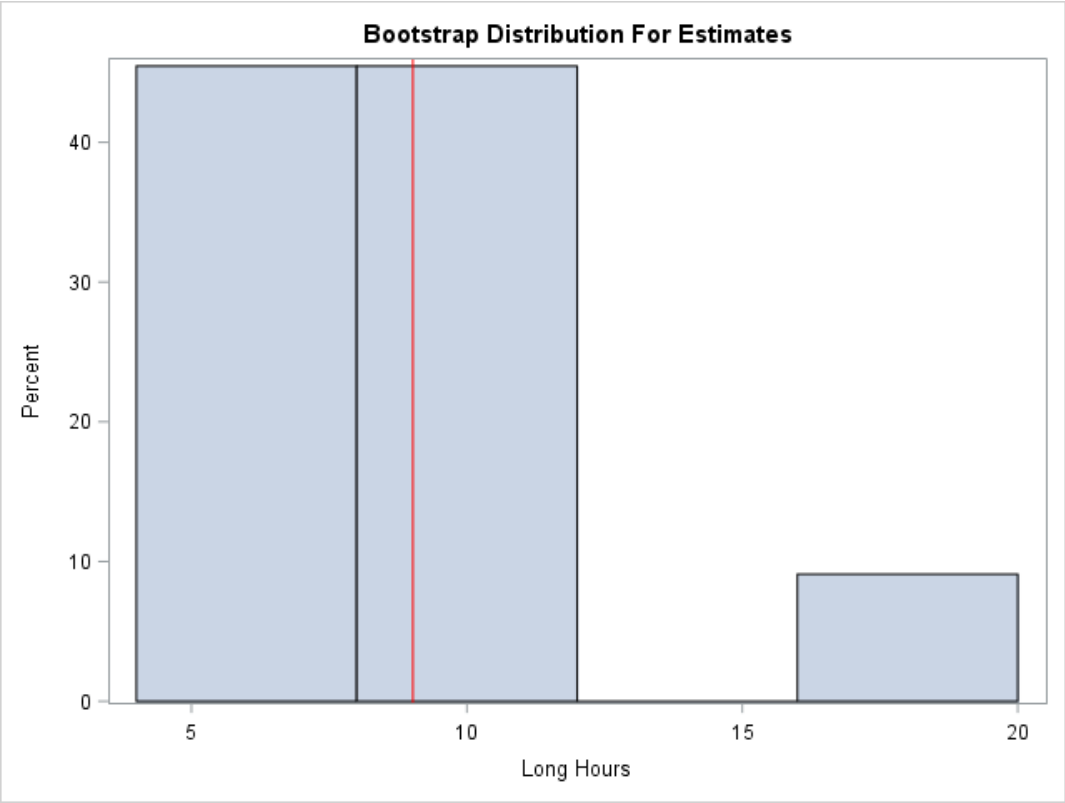


Figure 4.9. Bootstrap estimated distribution of long working hours

Long working hours was not selected by the exact logistic regression so there is no description of the results of the exact regression analysis presented here.

4.2.10 FOA

The estimated distribution of FOA from bootstrap sampling using stepwise logistic regression was greater than 0 (ranges from 3.37 to 4.65), as can be seen in Figure 4.10. An estimate greater than 0 gives an odds ratio of greater than 1, which indicates that there is a positive association between lack of FOA protection and negative publicity.

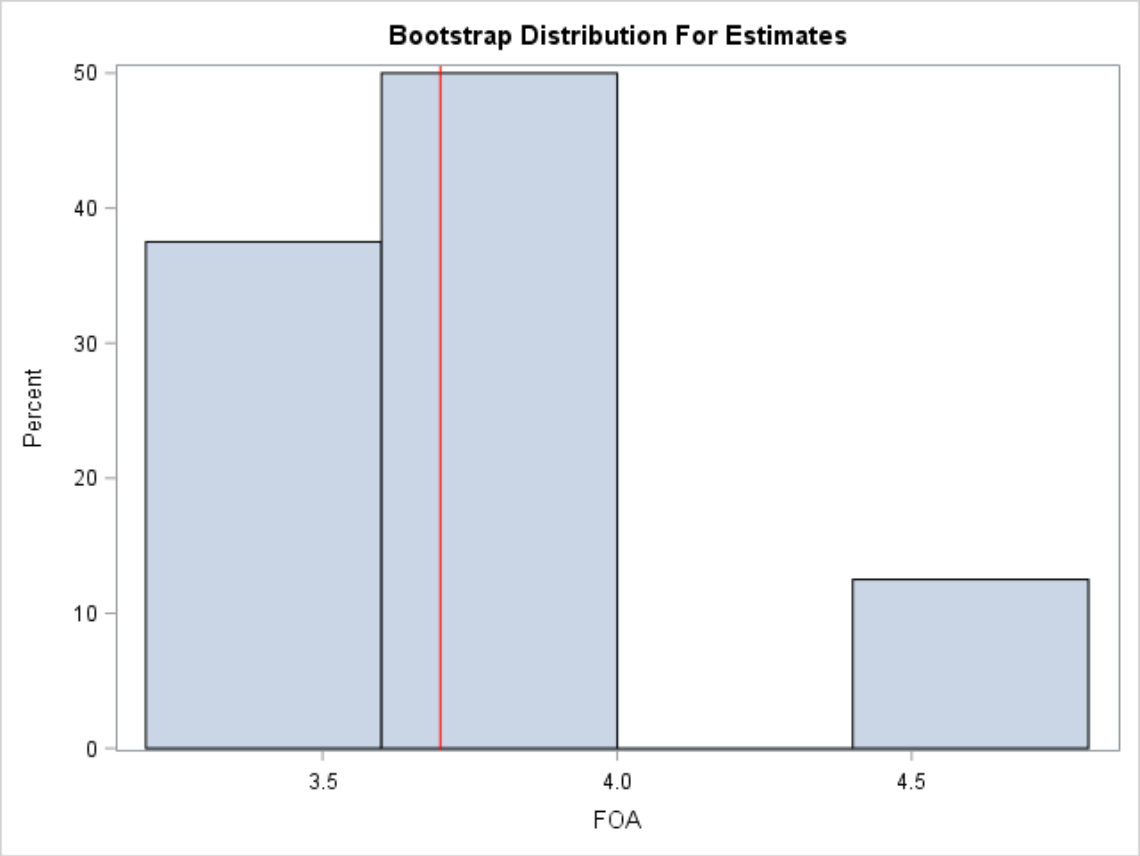


Figure 4.10. Bootstrap estimated distribution of FOA

FOA was not selected by the exact logistic regression so there is no description of exact analysis regression results presented here.

4.2.11 Clean water

The estimated distribution of clean water from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -14.78 to -14.78), as can be seen in Figure 4.11.

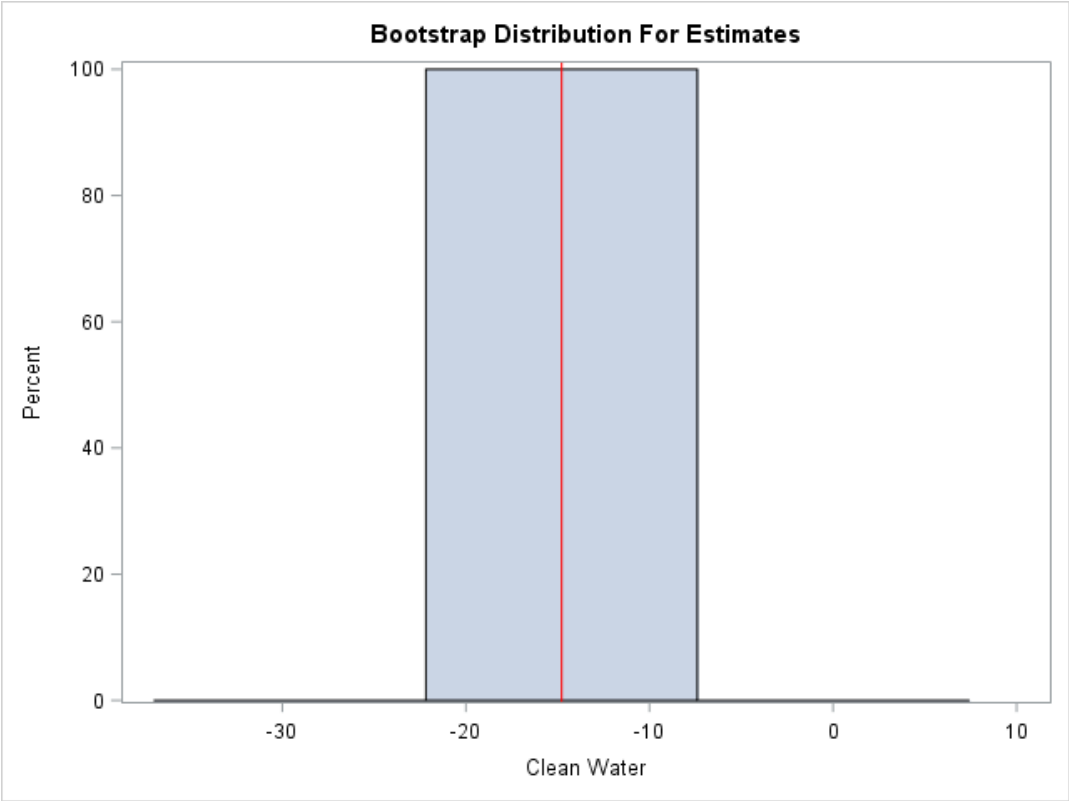


Figure 4.11. Bootstrap estimated distribution of clean water

An estimate less than 0 gives an odds ratio of less than 1, which indicates that there is a negative association between lack of clean water accessibility and negative publicity. But this finding is contradictory to the findings from exact logistic regression which suggested the lack of significance of clean water accessibility with negative publicity (p-value = 0.0769) (see Table 4.12).

Table 4.12

Exact Logistic regression for clean water

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Forced_Labor	Score	2.2223	0.0286	0.0214
	Probability	0.0143	0.4286	0.4214
Clean_Water	Score	4.2308	0.0769	0.0577
	Probability	0.0385	0.6538	0.6346

4.2.12 Buyer-Supplier Relationship

The estimated distribution of the buyer-supplier relationship from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -2.42 to -2.30), as can be seen in Figure 4.12. An estimate less than 0 gives an odds ratio of less than 1, which indicates that there is a negative association between the buyer-supplier relationship and negative publicity. This finding is consistent with the findings of stepwise logistic regression (see Table 4.6).

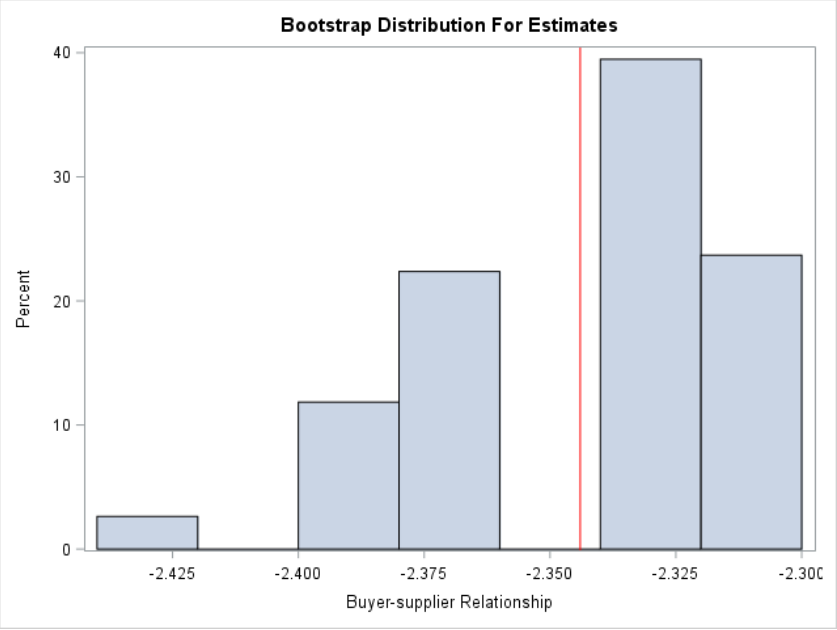


Figure 4.12. Bootstrap estimated distribution of buyer-supplier relationship

4.2.13 Certification

The estimated distribution of certification from bootstrap sampling using stepwise logistic regression was less than 0 (ranges from -2.24 to -2.19), as can be seen in Figure 4.13.

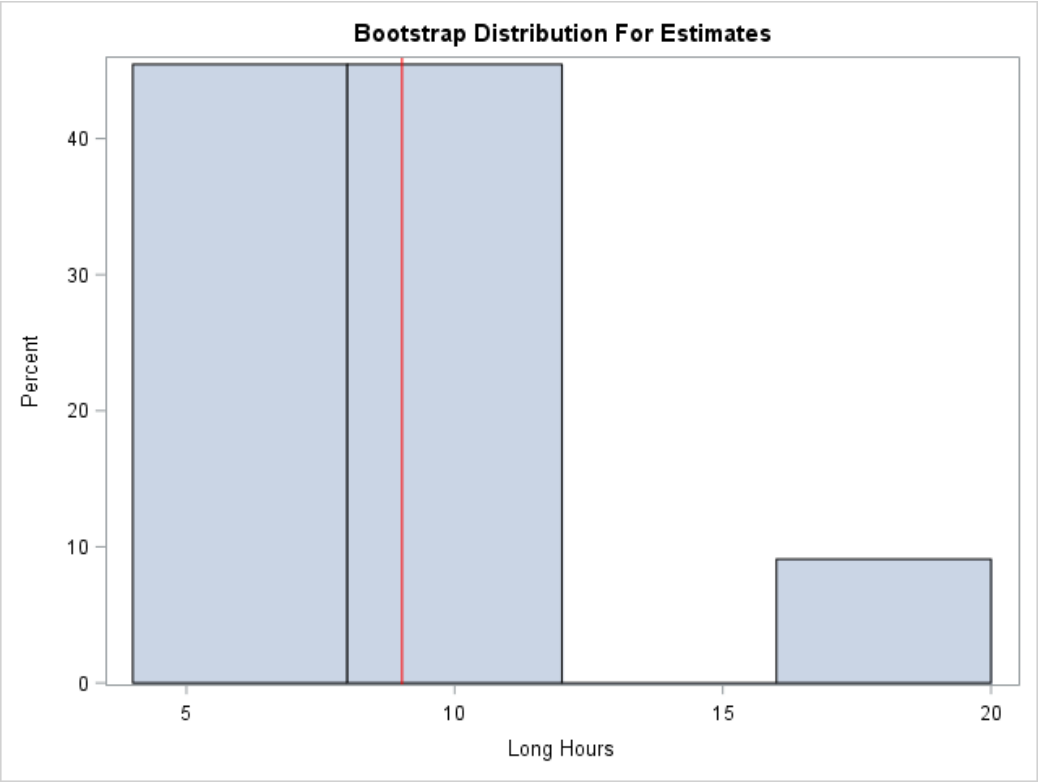


Figure 4.13. Bootstrap estimated distribution of certification

An estimate less than 0 gives an odds ratio of less than 1, which indicates that there is a negative association between safety certification and negative publicity based on bootstrap stepwise logistic regression. But this finding is contradictory to the findings from the exact logistic regression which suggested the lack of significance of certification with negative publicity (p-value=0.2006) (see Table 4.5).

Child labor and abuse were not discussed individually here because both of these variables were not selected by any of the logistic regression models.

In summary, only forced overtime, FOA, sanitation of toilets, long working hours, and cooperative inspection were consistent across all three logistic regression analyses. These factors were significantly associated with negative publicity for apparel factories in Bangladesh except for cooperative inspection which had a negative association with negative publicity. The buyer-supplier relationship was consistent across the bootstrap and the exact logistic regression analyses and has a negative association with negative publicity. Sanitation of the canteen did indicate some significance, based on the result from exact logistic regression; but these outcomes contradicted the findings of bootstrap estimates distribution, using stepwise logistic regression. The findings from the bootstrap stepwise logistic and the exact logistic regression were contradictory for certification and clean water accessibility, which therefore provided no compelling evidence that certification and clean water accessibility were associated with negative publicity. Child labor and abuse were not selected from any of the 1,000 bootstrap datasets for stepwise selection, which therefore provided no compelling evidence that child labor and abuse were associated with negative publicity.

The summary tables for these analyses can be seen in Tables 4.13a and 4.13b. The parameter estimates reported under the column for exact logistic and stepwise logistic were from the full sample dataset not from the under-sampled datasets (i.e., the parameter estimate reported for forced labor under exact logistic column came from full sample dataset V13).

In the table 4.13a, '-' sign means negative parameter estimates, '+' sign means positive parameter estimates, and '.' sign means no information.

Table 4.13a

Analysis summary for research objective 1

Variable	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Stepwise Logistic Regression findings**	**Exact Logistic Regression findings**
Worker Voluntary Feedback	-	•	•
Wages	-	•	•
Fire Safety	-	•	•
Sanitation of Toilets	+	+	•
Abuse	•	•	•
Child Labor	•	•	•
Worker Recommendation	-	-	-

Table 4.13a Analysis summary for research objective 1 (Continued)			
Variable	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Stepwise Logistic Regression findings**	**Exact Logistic Regression findings**
Long Working Hours	+	•	•
Sanitation of Canteen	•	•	+
Forced Overtime	+	+	+
FOA	+	•	•
Clean Water	-	•	•
Buyer-Supplier Relationship	-	•	-
Cooperative Inspection	-	-	-
Certification	-	•	•

Table 4.13b

Analysis summary for research objective 1

Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
Worker Voluntary Feedback	Range of negative estimate (i.e., -21.22 to -11.85)	No selection	No selection	Yes because of no inconsistent findings.	No because of negative parameter estimates
Wages	Range of negative estimate (i.e., -7.29 to -4.83)	No selection	No selection	Yes because of no inconsistent findings.	No because of negative parameter estimates

Table 4.13b Analysis summary for research objective 1 (Continued)					
Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
Fire Safety	Range of negative estimate (i.e., -4.38 to -4.38)	No selection	No selection	Yes because of no inconsistent findings.	No because of negative parameter estimates
Abuse	Lack of Significance	No Selection.	No Selection.	Lack of Significance	No because of no evidence of association
Child Labor	Lack of Significance	No Selection.	No Selection.	Lack of Significance	No because of no evidence of association

Table 4.13b Analysis summary for research objective 1 (Continued)					
Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
Worker Recommendation	Range of negative estimate (i.e., -15.6 to -3.3)	Negative estimate (-4.127) and odds ratio of less than 1. (i.e., 0.959)	Negative estimate (-4.0848) and odds ratio of less than 1. (i.e., 0.9599)	Yes	No because of negative parameter estimates
Long Working Hours	Range of positive estimate (i.e., 6.3 to 19.28)	No selection	No selection	Yes because of no inconsistent findings	Yes, because it was selected by bootstrap logistic regression

Table 4.13b Analysis summary for research objective 1 (Continued)					
Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
Sanitation of Canteen	Can be either positive or negative as estimate 0 fall within the distribution (i.e., -5.8 to 4.5)	Positive estimate (2.4402) and odds ratio of greater than 1. (i.e.,11.47)	No selection	No because of inconsistent findings	No because of no evidence of association
Forced Overtime	Range of positive estimate (i.e., 4.01 to 14.7)	Positive estimate (4.53) and odds ratio of greater than 1.	Positive estimate (1.6988) and odds ratio of > 1.	Yes	Yes, because it was selected by all three logistic models

Table 4.13b Analysis summary for research objective 1 (Continued)					
Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
FOA	Range of positive estimate (i.e., 3.37 to 4.65)	No selection	No selection	Yes because of no inconsistent findings	Yes, because it was selected by bootstrap estimate using stepwise logistic regression
Clean Water	Range of negative estimate (i.e., -14.78 to -14.78)	Lack of Significance as score test p value was greater than 0.05	Lack of Significance	No because of inconsistent findings	No because of no evidence of association

Table 4.13b Analysis summary for research objective 1 (Continued)					
Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
Buyer-Supplier Relationship	Range of negative estimate (i.e., -2.42 to -2.3)	Negative estimate (-2.33) and odds ratio of less than 1. (i.e., 0.097)	No selection	Yes because of no inconsistent findings	Negative association with negative publicity
Cooperative Inspection	Range of negative estimate (i.e., -2.42 to -2.30)	Negative estimate (-1.3559) and odds ratio of less than 1. (i.e., 0.257)	Negative estimate (-1.3122) and odds ratio of less than 1. (i.e., 0.269)	Yes	Negative association with negative publicity

Table 4.13b Analysis summary for research objective 1 (Continued)					
Variables	**Stepwise Logistic Regression findings based on bootstrap sampling**	**Exact Logistic Regression findings**	**Stepwise Logistic Regression findings**	**Consistent findings**	**Association with Negative Publicity**
Certification	Range of negative estimate (i.e., -2.24 to -2.19)	Lack of Significance as p value was 0.1076	Lack of Significance	No because of inconsistent findings	No because of no evidence of association

4.3 Factories receiving negative publicity versus those not receiving negative publicity

This section contains analysis for Research Objective 2. Three steps were taken to determine whether factories receiving negative publicity contained any specific pattern, based on workers feedback. The first step was to plot worker responses by putting the worker response proportion (which is from 0 to 1 with values closer to 1 means more compliant) on the x-axis. The second step was to manually analyse open-ended responses to determine the distribution of frequent issues faced by factory workers among factories receiving negative publicity. The third step was to plot worker sentiment across sample factories.

4.3.1 Plots of Worker Responses

In this section, worker response charts of each category of worker level indicators (i.e., worker responses) and bar charts of each category of factory level indicators are presented and interpreted. For worker responses charts, the *x-axis* contained the worker responses ranging from '0' to '1' where responses close to '1' represent workers complaints and responses close to '0' represent workers satisfactory responses. The 'red' circle represents factories with the "Presence of Negative Headline" or negative publicity as negative publicity is defined as the presence of negative headline in this dissertation. Similarly, the 'blue' circle represents factories with the "Absence of Negative Headline". The *y-axis* in the worker responses charts containing the response variable publicity with binary responses: 'presence' and 'absence' of negative headlines. The Wilcoxon test was used to test whether there was a difference in the median responses on worker issues by publicity (presence or absence of negative headlines). The purpose of the worker response charts was to show the distribution of worker issues by type of publicity (presence or absence of negative headlines). For bar charts, the binary responses are on the *x-axis* and the *y-axis* contains the "Number of Factories". The 'red' bar represents factories with the "Presence of Negative Headline" or negative publicity, as negative publicity is defined as the presence of negative headline in this dissertation. Similarly, the 'blue' bar represents factories with the "Absence of Negative Headline". A chi square test was used to test the association between sentiments of apparel factories and negative publicity.

4.3.1.1 Fire Safety

The majority of negative headlines appeared in the factories where workers responses were satisfactory on the fire safety question (between the proportion 0 and 0.5, where 0 means satisfactory and 1 means unsatisfactory or complaints response), as can be seen in Figure 4.14.

The Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on fire safety (z-value= -1.09, p= 0.2755).

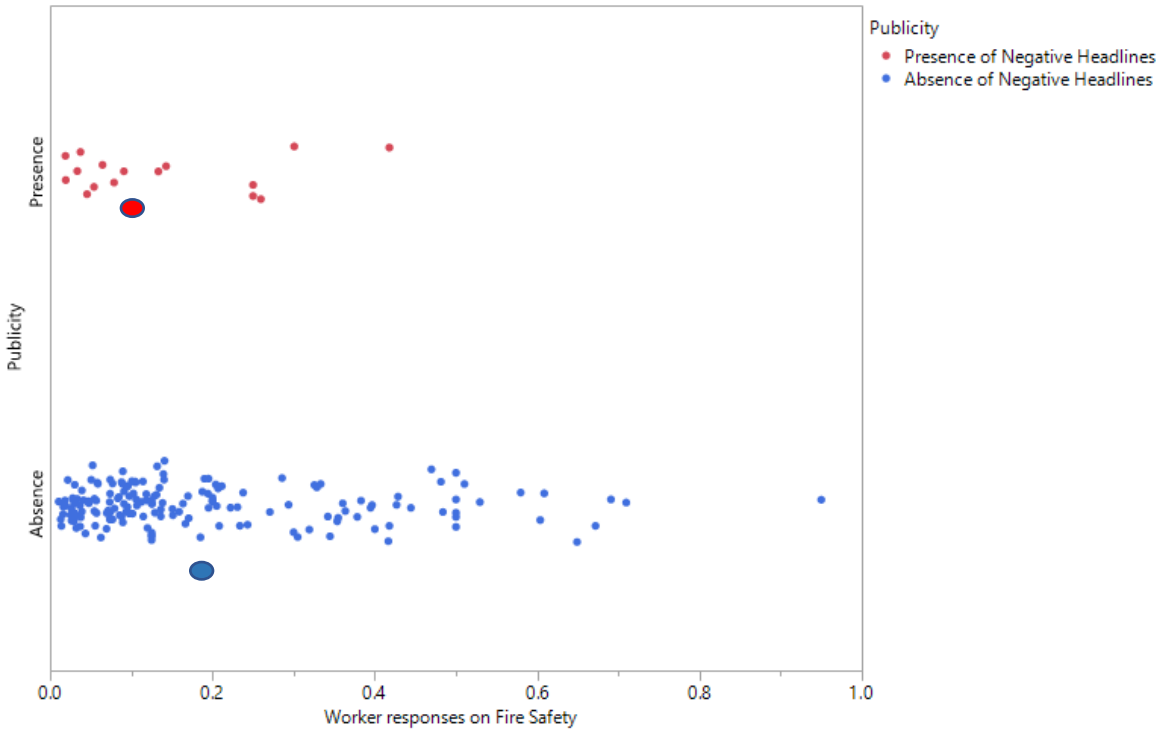


Figure 4.14. Factory distribution by fire safety

4.3.1.2 Worker Voluntary Feedback

All negative headlines arose in the factories where workers were not willing to give open-ended feedback (between proportion 0 and 0.15), as can be seen in Figure 4.15. This means that negative headlines occurred even when workers did not want to participate in an open-ended survey question to say anything additional about working conditions inside the factories. However, the Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on worker voluntary feedback (z-value = -1.27, p-value= 0.20). Therefore, there is no difference in workers' willingness to participate in a voluntary open-ended survey question and type of factory publicity.

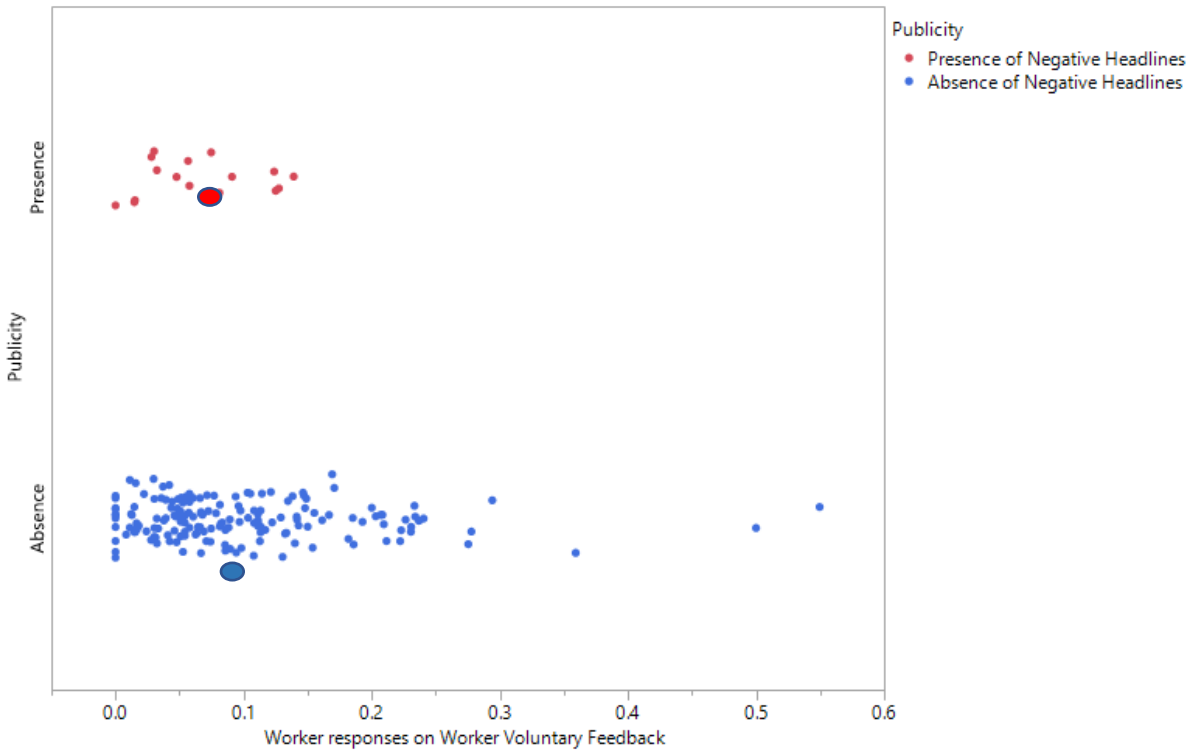


Figure 4.15. Factory distribution by workers voluntary feedback

4.3.1.3 Long working hours

The majority of negative headlines showed up in factories where worker responses on long working hours were satisfactory (between the proportion 0.1 and 0.6), as can be seen in Figure 4.16. This means that negative headlines occurred even when workers got frequent rest breaks during long working hours inside factories. However, the Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on long working hours (z= 1.246, p-value= 0.212).

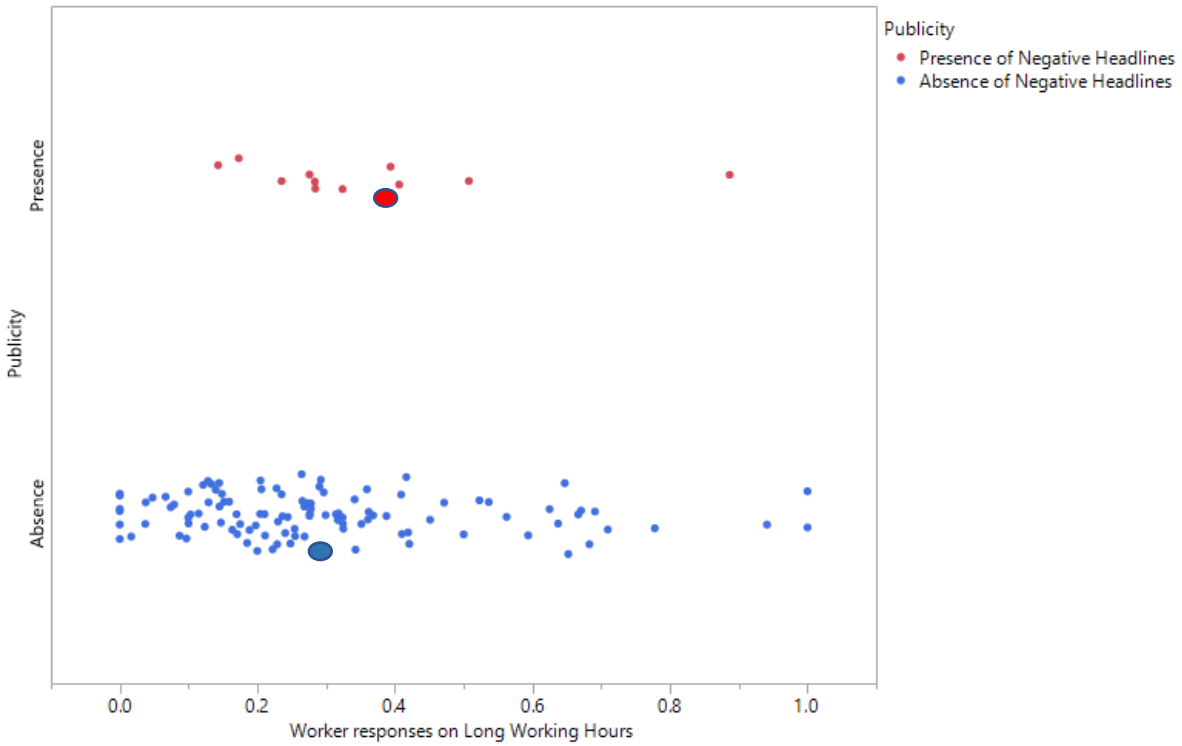


Figure 4.16. Factory distribution by long working hours

4.3.1.4 Abuse

The majority of negative headlines occurred in the factories where worker responses on abusive treatment were satisfactory (with proportion of less than 0.5), as can be seen in Figure 4.17. This means that negative headlines occurred even when workers did not face any abusive conditions inside factories. However, the Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on abuse (z= -0.886, p-value= 0.3741).

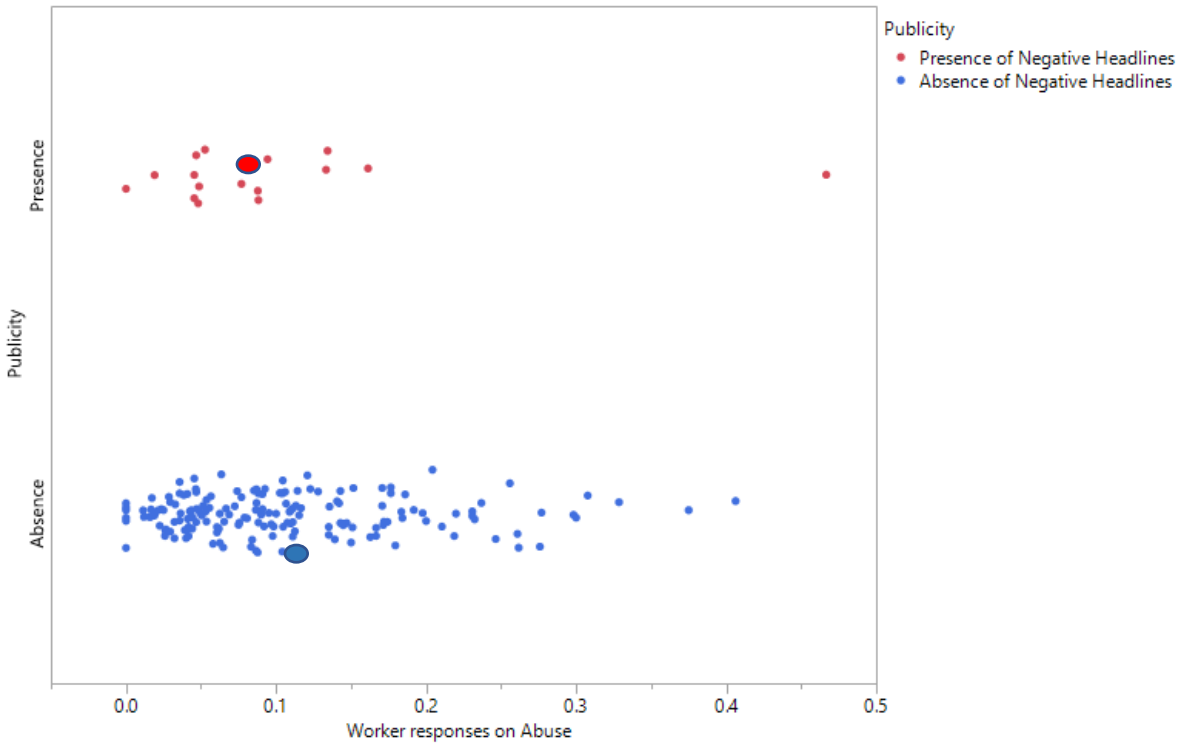


Figure 4.17. Factory distribution by abuse

4.3.1.5 Child Labor

The majority of negative headlines showed up in the factories where worker responses on the existence of child labor inside a factory were satisfactory (with proportion of less than 0.4), as can be seen in Figure 4.18. This means that negative headlines occurred even if there is no presence of child labor inside factories. However, the Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on child labor (z-value= 0.221, p-value= 0.825).

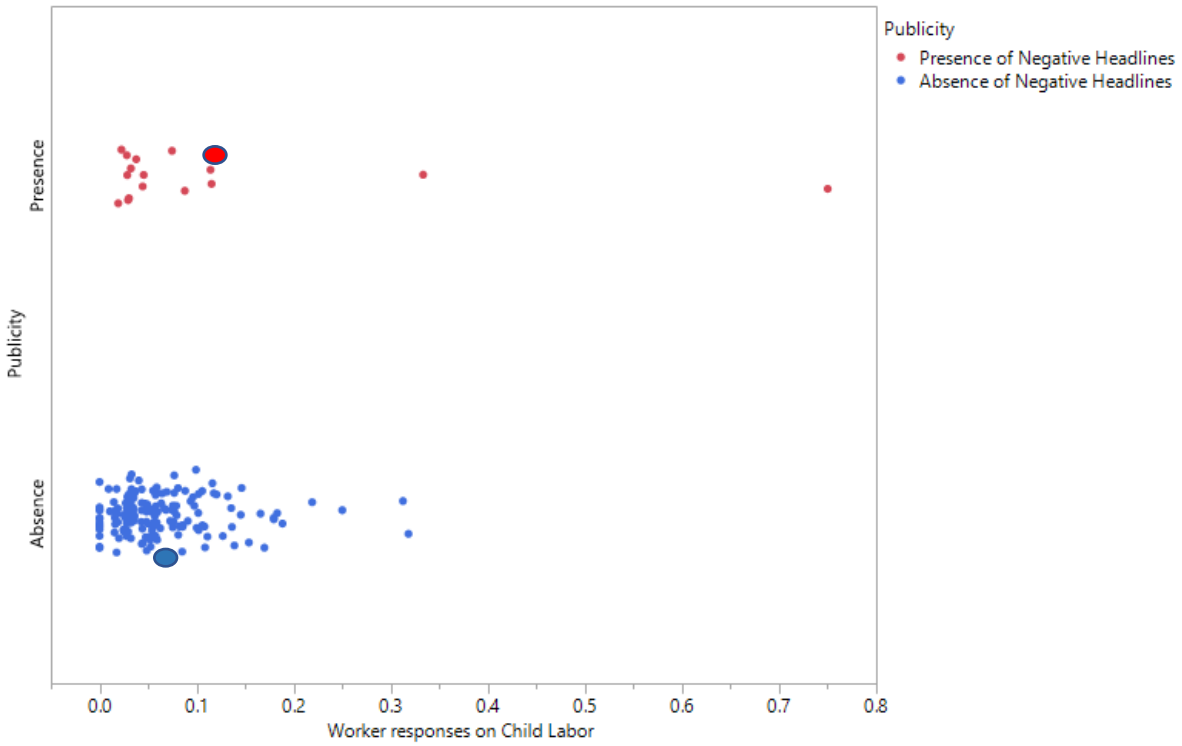


Figure 4.18. Factory distribution by child labor

4.3.1.6 Wages

All negative headlines showed up in the factories where worker responses on the delay in wages issues were satisfactory (with proportion of less than 0.45), as shown in Figure 4.19.

This means that negative headlines occurred even when workers did not face a delay in their monthly wages or annual bonuses. The Wilcoxon test indicated this was a significant difference between factories with negative headlines and factories without negative headlines on wages (z value= 2.33, p-value= 0.0197).

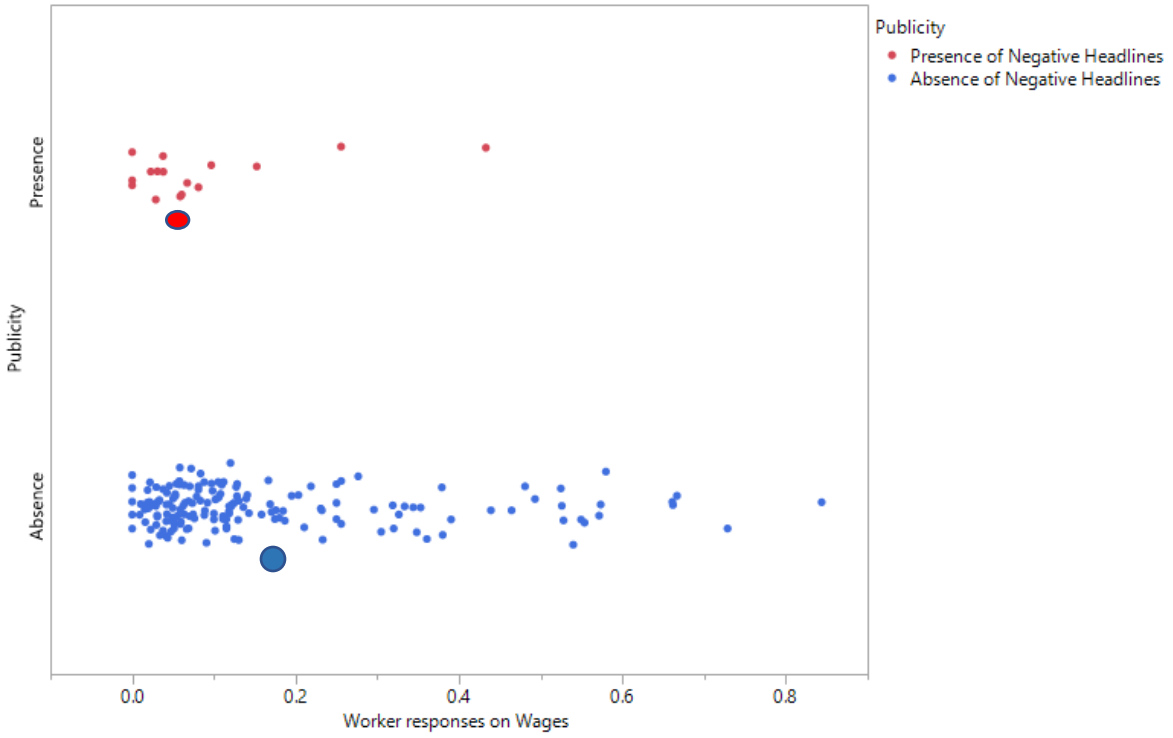


Figure 4.19. Factory distribution by wages

4.3.1.7 Sanitation of the canteen

All negative headlines showed up in the factories where worker responses on sanitation issues in the canteen were satisfactory (with responses between 2.5 and 3.75, where responses close to 4 mean no complaint), as can be seen in Figure 4.20. This means that negative headlines occurred even when workers faced no sanitation issues related to canteens inside factories. However, the Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on sanitation of the canteen (z-value= 1.22, p-value= 0.2195).

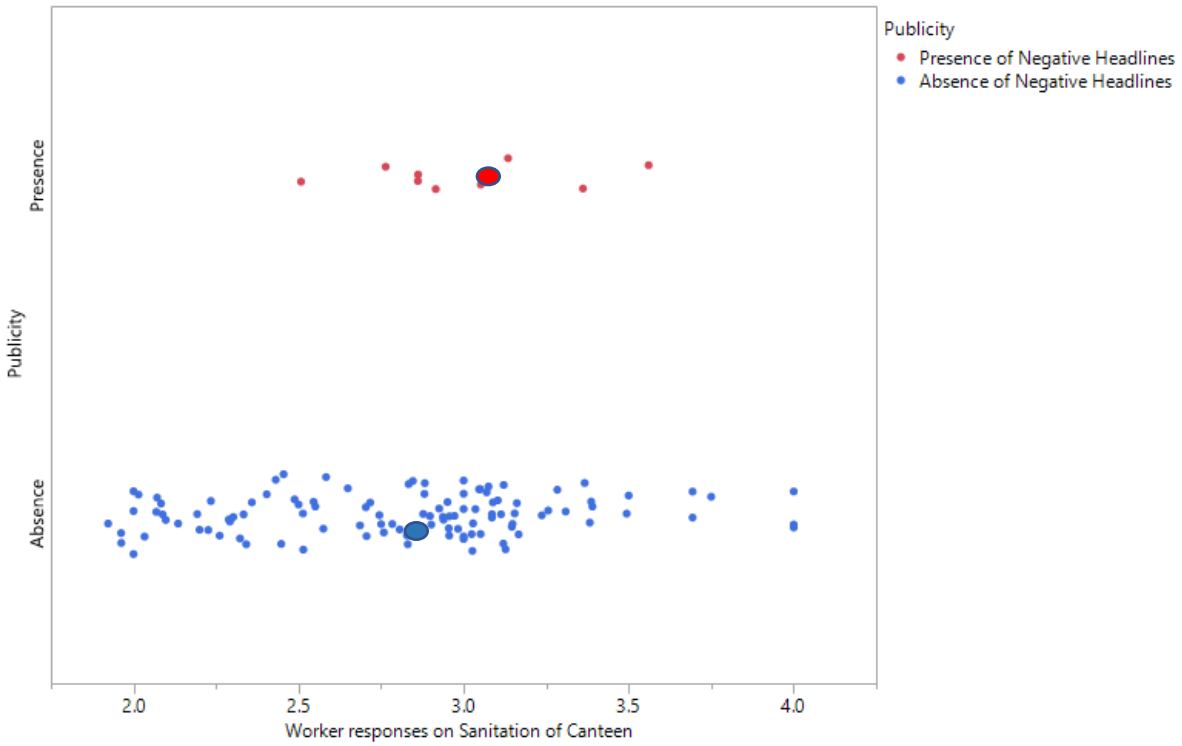


Figure 4.20. Factory distribution by sanitation of the canteen

4.3.1.8 Sanitation of toilets

All negative headlines showed up in the factories where worker responses on sanitation issues related to toilets were satisfactory (with proportion between 2.5 and 3.5, where responses close to 4 mean no complaint), as can be seen in Figure 4.21. This means that negative headlines may occur even when workers faced less sanitation issues related to toilets inside factories. The Wilcoxon test indicated there is a significant difference between factories with negative headlines and factories without negative headlines on the sanitation of toilets (z-value 2.87, p-value 0.0040).

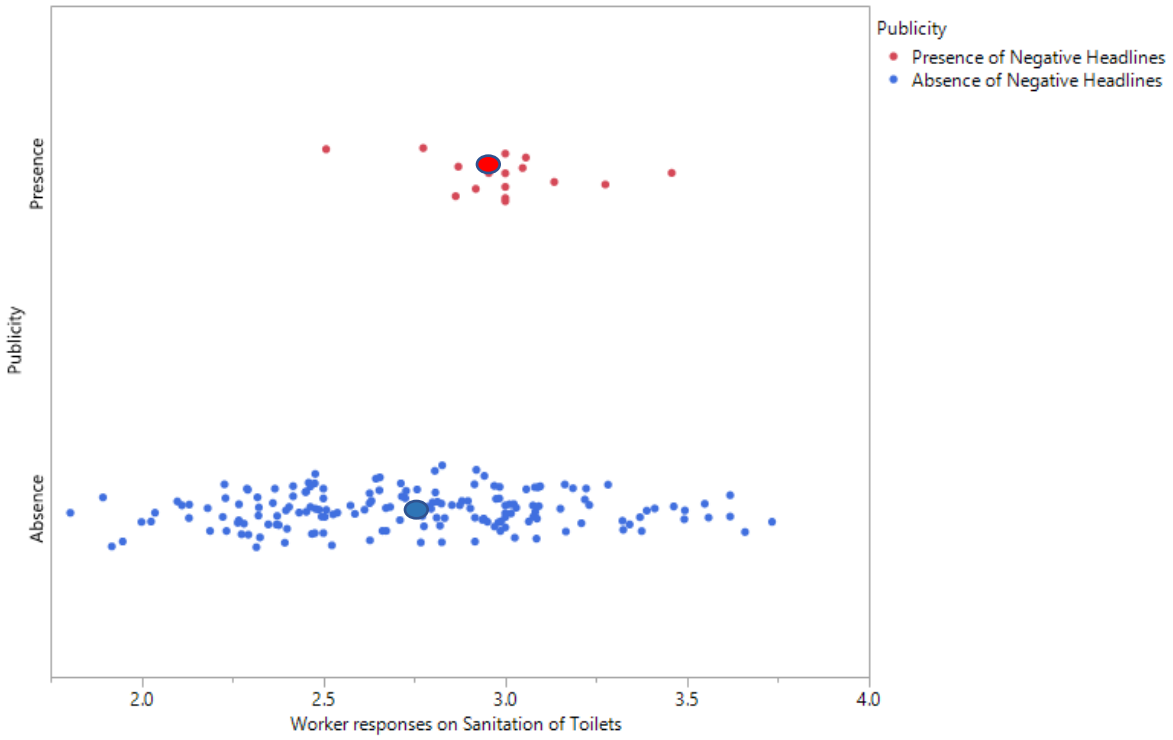
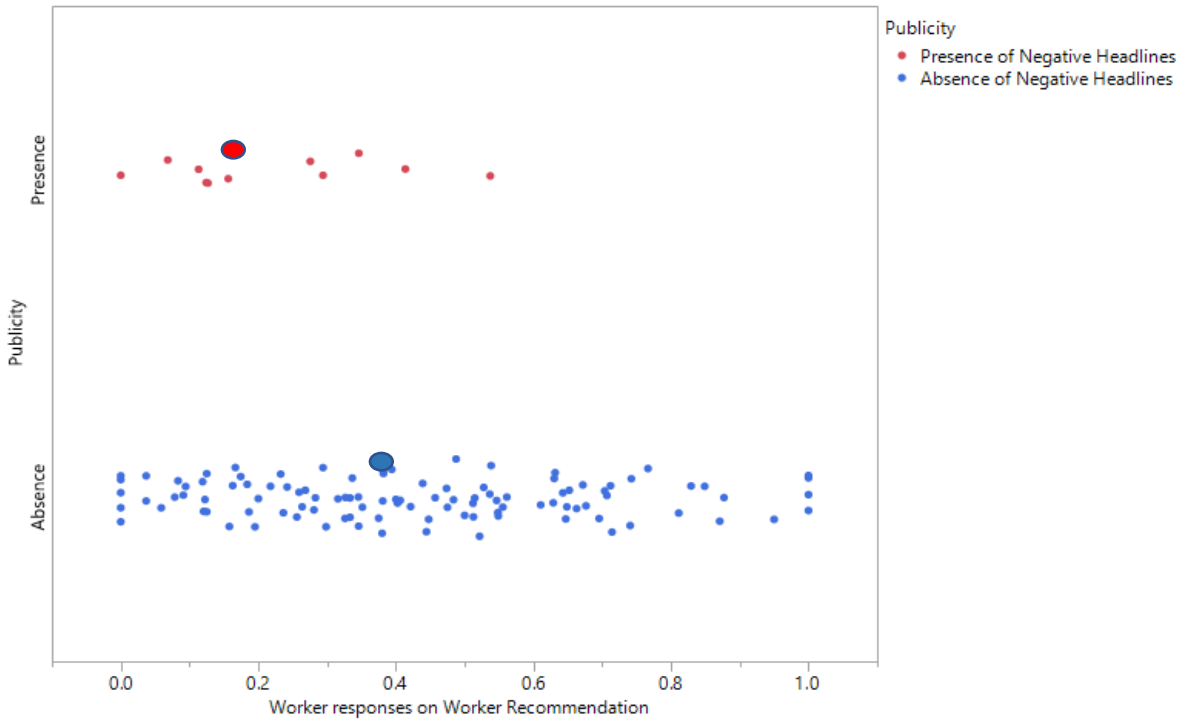


Figure 4.21. Factory distribution by sanitation of toilets

4.3.1.9 Worker Recommendations

All negative headlines showed up in factories where workers were willing to recommend their factories to friends and family (with a proportion of less than 0.6) as seen in Figure 4.22. This means that negative headlines occurred even when workers were willing to recommend the factory where they were employed to family members and friends. The Wilcoxon test indicated this was a significant difference between factories with negative headlines and factories without negative headlines (z-value= -2.564, p-value= 0.0103).



.

Figure 4.22. Factory distribution by worker recommendation

4.3.1.10 Freedom of Association

The distribution of negative headlines covered both satisfactory and unsatisfactory responses on FOA protection (between the proportion 0 and 1, where 0 means satisfactory and vice versa), as can be seen in Figure 4.23. The Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on FOA (z-value= 0.806, -value= 0.42).

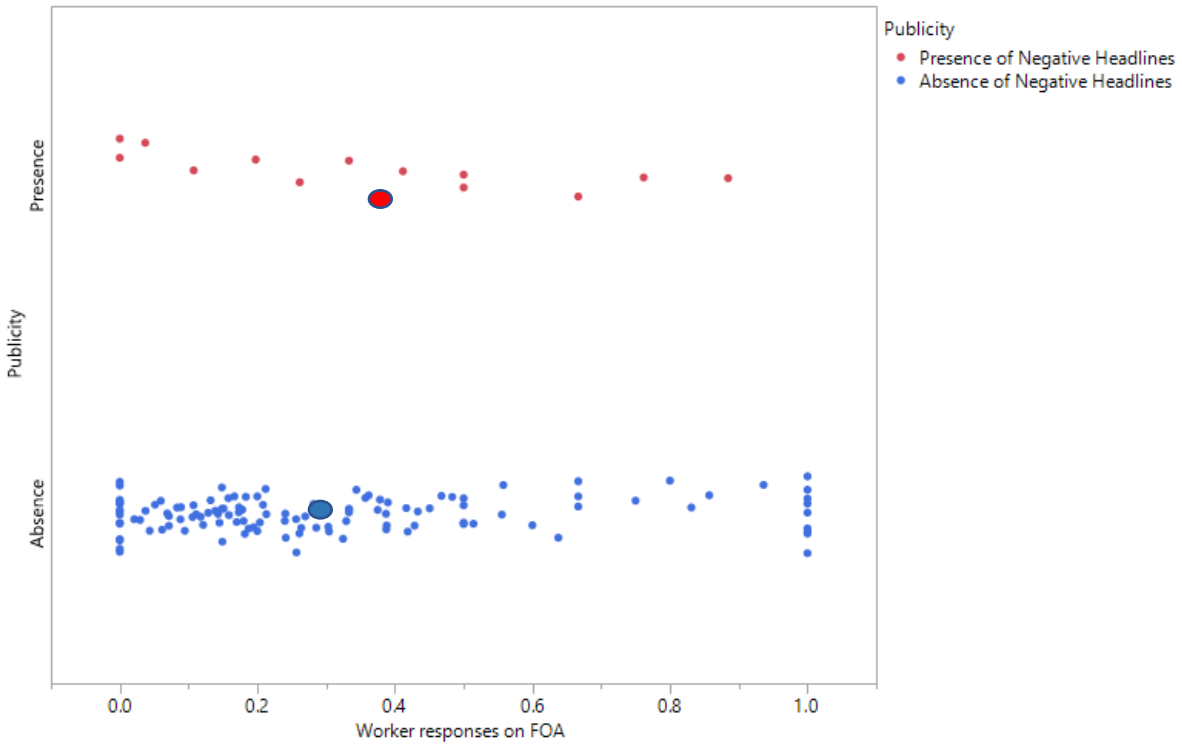


Figure 4.23. Factory distribution by freedom of association

4.3.1.11 Clean Water Accessibility

The majority of negative headlines showed up in factories where worker responses on clean water accessibility issue were satisfactory (with a proportion of less than 0.2), as can be seen in Figure 4.24. This means that negative headlines occurred even when workers did not face clean water accessibility issues. However, the Wilcoxon test indicated there was no significant difference between factories with negative headlines and factories without negative headlines on clean water accessibility (z-value= -0.9285, p-value= 0.3531).

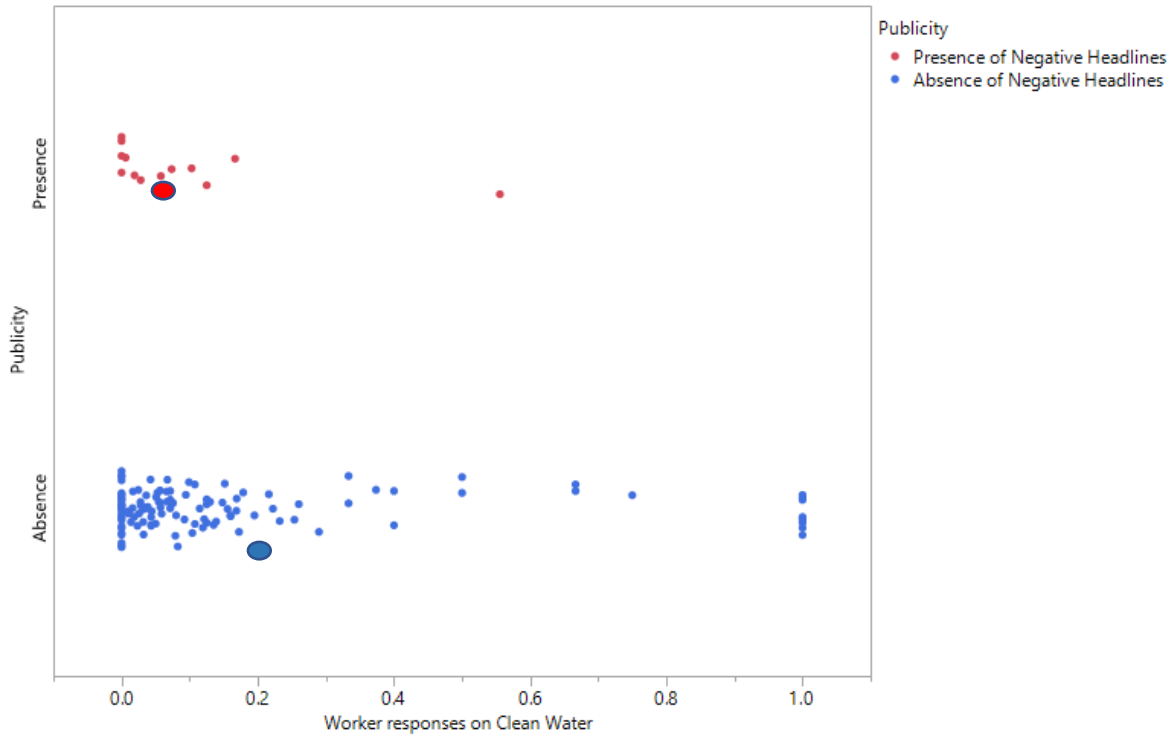


Figure 4.24. Factory distribution by clean water accessibility

4.3.1.12 Forced Overtime

Negative headlines showed up in factories where worker responses on forced overtime issues were both satisfactory and unsatisfactory. The Wilcoxon test indicated this was a significant difference between factories with negative headlines and factories without negative headlines (z-value= 2.56, p-value= 0.0105).

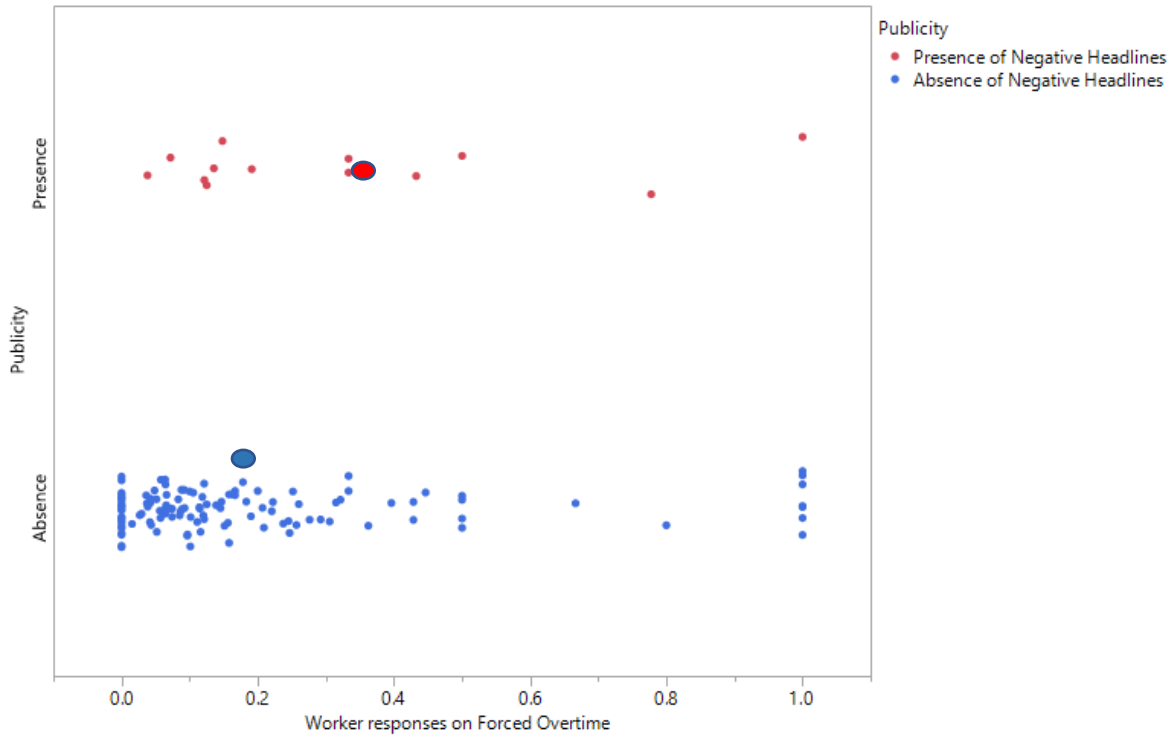


Figure 4.25. Factory distribution by forced overtime

4.3.1.13 Buyer-Supplier Relationship

The majority of negative headlines showed up in the factories that were either Tier 1 or Tier 2 suppliers, as seen in Figure 4.26. However, the statistical findings of the bootstrap stepwise logistic regression and the exact logistic regression (see Table 4.1 and 4.5) were that close buyer-supplier ties (i.e., tier1 and tier2) had a negative association with negative publicity. This means that if suppliers are visible to the brands, and brands know about where their product is manufactured, then factories with Tier 1 and Tier 2 status may lead to the absence of negative publicity. Therefore, we concluded that there is an association between stronger buyer-supplier relationship and the absence of negative publicity.

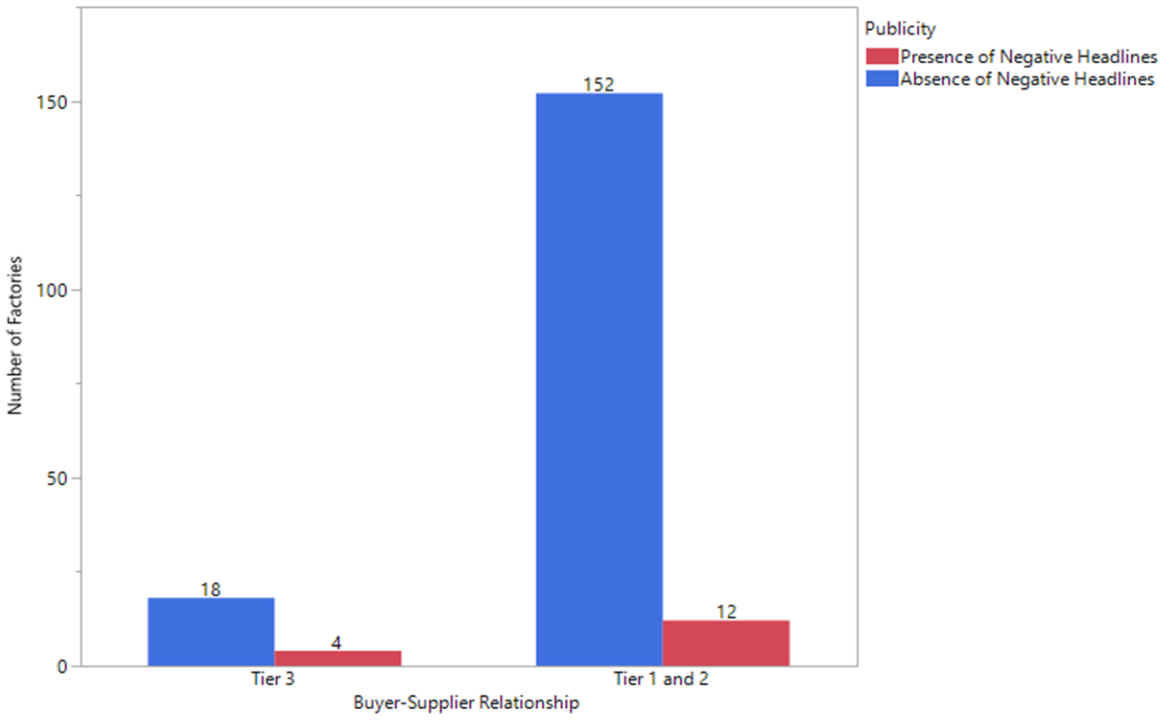


Figure 4.26. Factories distribution by buyer-supplier relationship

4.3.1.14 Certification

The majority of negative headlines showed up in the factories that were not certified by either WRAP, SA 8000, or WRC as seen in Figure 4.27. Therefore, lack of certification may be a good indicator that factories will receive negative publicity. This insight is consistent with the findings of bootstrap stepwise logistic regression (see Table 4.1) where certified factories have a negative association with negative publicity. But since there was a contradiction in the findings between the bootstrap stepwise logistic and the exact logistic regression, we concluded that there is no evidence of association between certified apparel factories and negative publicity.

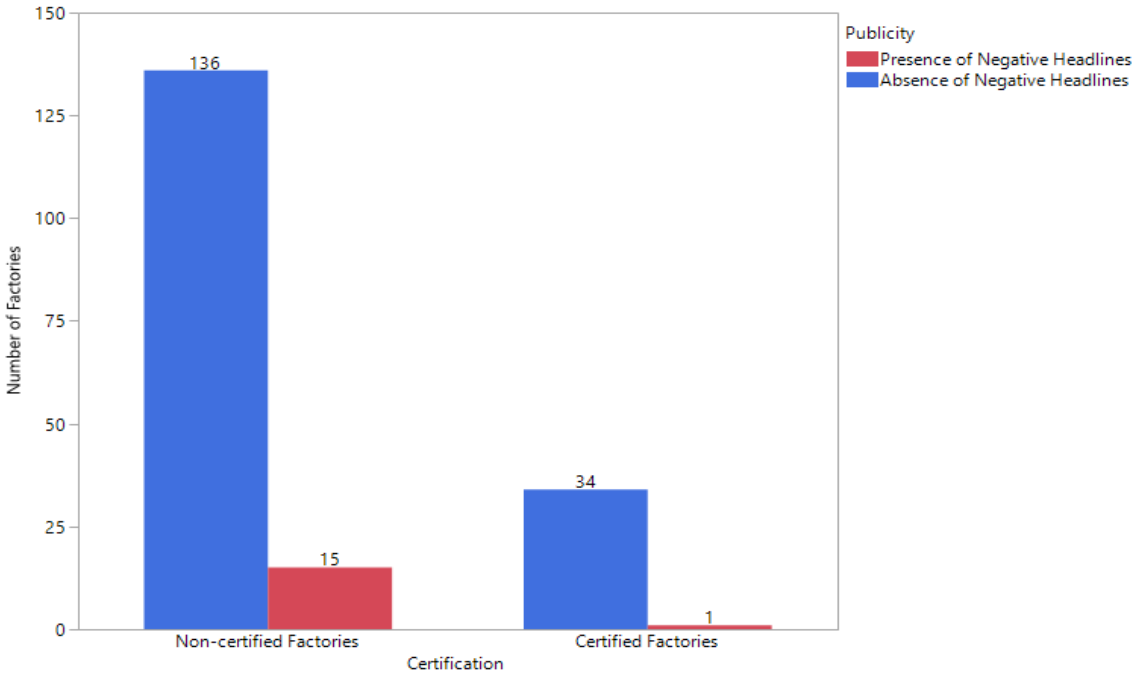


Figure 4.27. Factory distribution by certification

4.3.1.15 Cooperative Inspection

The majority of negative headlines showed up in factories that did not follow an announced approach to inspection, as can be seen in Figure 4.28. Therefore, announced approach to inspection helps factories avoid negative publicity, which is consistent with the findings of all three regression analyses (see Table 4.1, 4.3, and 4.5) where announced approach to inspection had a negative association with negative publicity. Therefore, we concluded that there is an association between announced approach to feedback crowdsourcing and the absence of negative publicity.

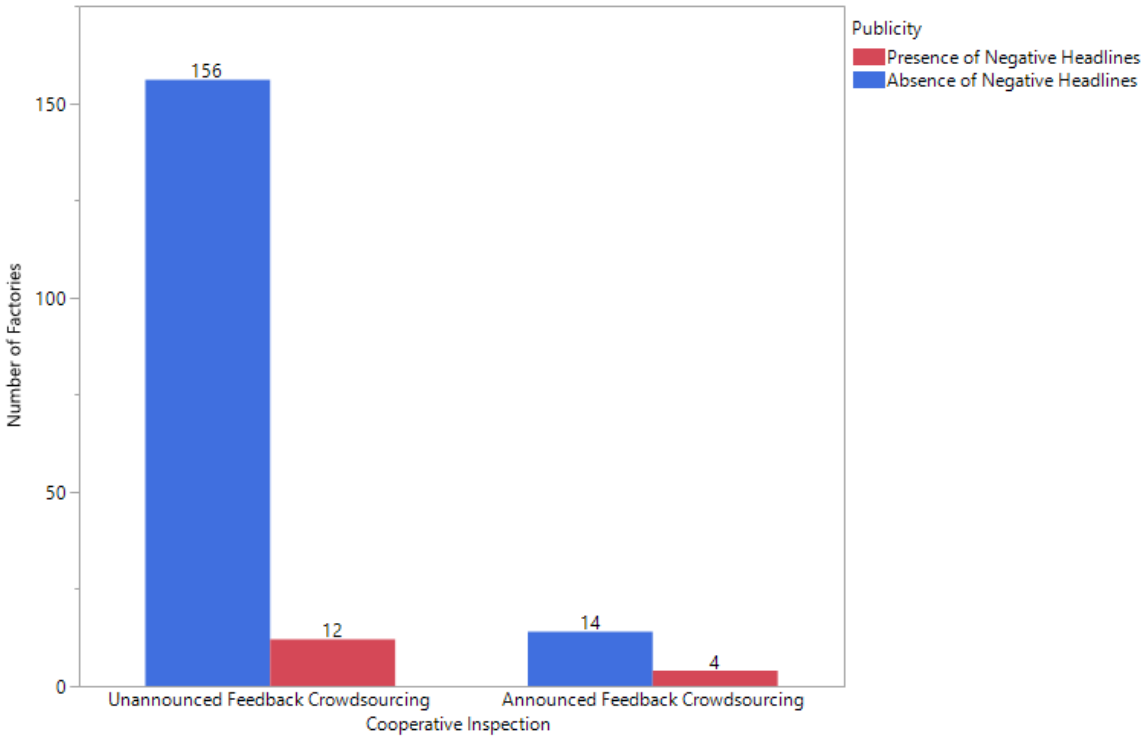


Figure 4.28. Factory distribution by cooperative inspection

4.3.2 Triggers of negative publicity

Open-ended responses from apparel factory workers were quantified manually by reading all feedback on factories receiving negative publicity. Then the issues were listed with the frequency of factories where workers faced those issues. The table can be seen below.

Table 4.14

Issues among factories receiving negative publicity

Issues	**Frequency of negative factories**	**Number of workers that identified each specific issue**
Delay in Wages	5	11
Forced Overtime	3	7
All good (no grievance)	5	13
Verbal Abuse	5	4
Physical Abuse	2	2
FOA	1	3
Long Working Hours	3	5
Clean Water accessibility	1	1
Child Labor	1	1
Sanitation of toilets	1	1
Inspection influenced by factory management	2	3

As can be seen in the table above, forced overtime, FOA, and long hour's issues were present in the list of worker grievances in factories receiving negative publicity. This is

consistent with the findings of logistic regression in the previous section. Delay in wages, verbal abuse, and no worker grievances were the leading issues categories, based on workers' open-ended feedback. These issue categories contradict the findings of the logistic regression models. One possible explanation of this could be the influence of factory management as mentioned by workers in two factories receiving negative publicity. It is possible that workers responded to the survey in favour of factory management despite facing issues including delay in wages and verbal abuses. The risk of factory influence is one of the challenges that a workplace feedback system may face, which is discussed in chapter 5 in detail.

Some additional information was also extracted using the open-ended feedback data. Most of the negative headlines occurred in factories where workers gave fewer than 5 open-ended responses per factory, as can be seen in Figure 4.29.

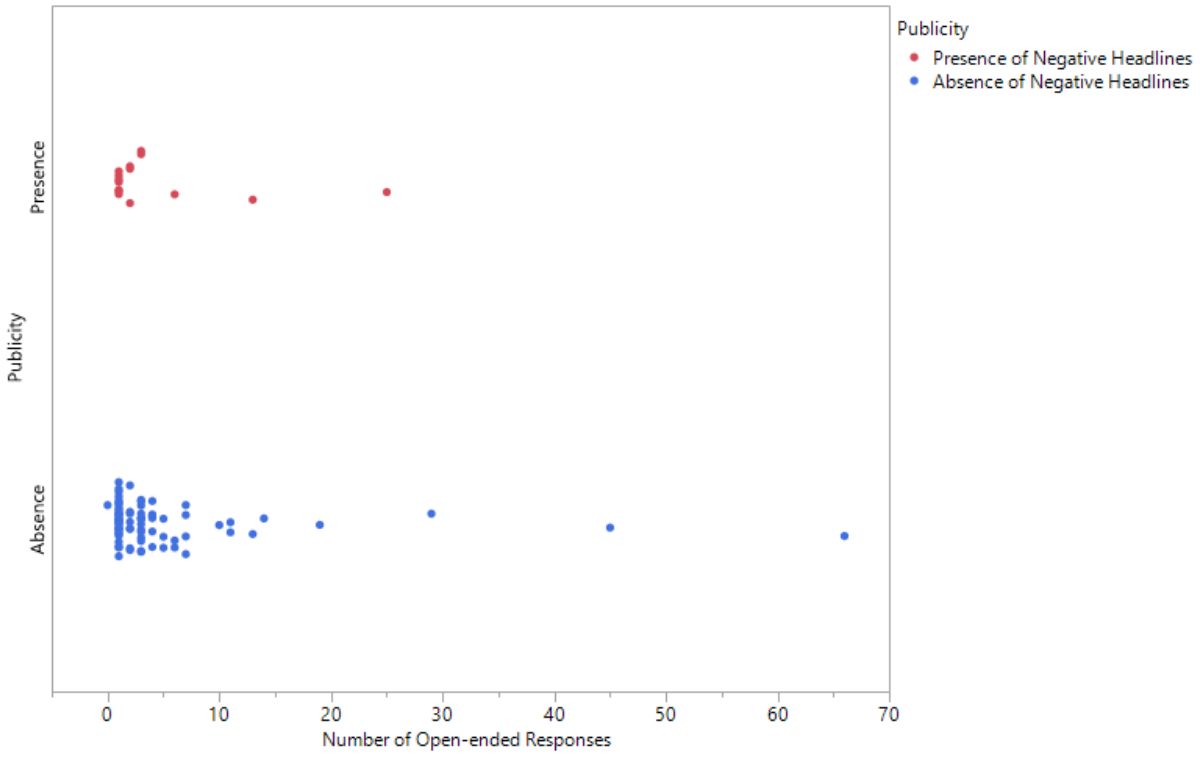


Figure 4.29. Factory distribution by number of open-ended responses

This implies that even a few responses per factory can provide critical information that may be utilized to address worker grievances. Finally, a sentiment score was calculated, as explained in chapter 3, to see whether negative publicity came from negative sentiment factories. Most of the negative headlines occurred in factories where the sentiment score was less than 0 (Chi-square value= 7.625, p-value= 0.0058), as shown in the figure below.

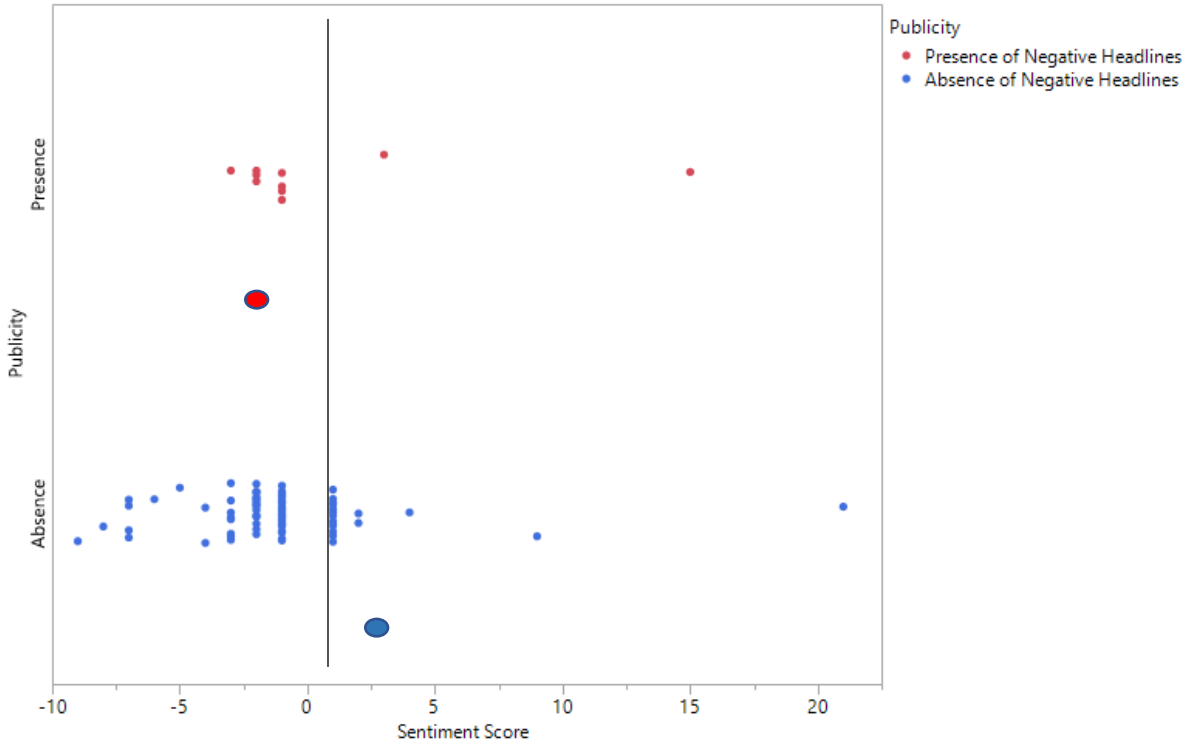


Figure 4.30. Factory distribution by sentiment score

This implies the importance of worker sentiment about their workplace.

Factories with negative publicity were gathered using local and international news sources. These news sources mentioned the triggering factors behind each negative headline. The frequent triggering factors mentioned in negative news articles (see Appendix C) included the fire safety concerns, low wages, and forced overtime. The summary of the conclusion and the key takeaways from both research objectives are presented in Table 4.15.

Table 4.15

Conclusion and the key takeaways from both research objectives

Variables	**Conclusion**	**Key Takeaways**
Worker Voluntary Feedback	Lack of evidence of association between workers' willingness to participate in a voluntary open-ended survey question about an apparel factory and negative publicity	Workers' willingness to participate in a voluntary open-ended survey question about an apparel factory is a potential indicator of the absence of negative publicity because more the workers express about their working conditions, the more it will provide visibility to suppliers and brands to address workers issues and to eventually control reputational damage.
Wages	Some evidence of association between a delay in wages in an apparel factory and negative publicity	Workers from negative factories showed satisfaction on delay in wages issues based on survey responses. But the workers who participated in open-ended questions identified both delay in wages and low wages. So, workers can respond differently in open-ended responses which can give brands and suppliers a new layer of information that may need more investigation. Low wages mentioned by the news publishers as the triggering of negative publicity in 2016 which shows contradiction.

Table 4.15 Conclusion and the key takeaways from both research objectives (Continued)		
Variables	**Conclusion**	**Key Takeaways**
Fire Safety	Lack of evidence of association between fire safety violations in an apparel factory and negative publicity	Workers from negative factories showed satisfaction on fire safety issues based on survey responses including fire safety. Interestingly, these findings contradict with the triggering factors published by local and international news publisher in 2016 where fire safety issues were one of the biggest triggering factors of negative publicity. This contradiction gives an extra layer of information to both brands and suppliers.
Sanitation of Toilets	Lack of evidence of association between poor sanitation conditions of the toilets and negative publicity	The statistical analysis did not provide evidence about the association between poor sanitation conditions of the toilets and negative publicity, but it was mentioned by factory workers as possible trigger of negative publicity in open ended responses.
Abuse	Lack of evidence of association between abusive working conditions and negative publicity	Abuse did not provide statistical evidence of association with negative publicity, but it was mentioned by factory workers as possible trigger of negative publicity in open ended responses.

Table 4.15 Conclusion and the key takeaways from both research objectives (Continued)		
Variables	**Conclusion**	**Key Takeaways**
Child Labor	Lack of evidence of association between child labor presence inside an apparel factory and negative publicity	Negative headlines occurred even if there is no presence of child labor inside factories. So, child labor did not provide statistical evidence of association with negative publicity.
Worker Recommendation	Lack of evidence of association between worker recommendation and negative publicity	Negative headlines occurred even when workers were willing to recommend the factory where they were employed to family members and friends. This could potentially happen due to the influence of factory management on survey responses. This finding need more investigation.
Long Working Hours	Some evidence of association between long working hours in an apparel factory and negative publicity	Long working hours with no breaks inside an apparel factory can lead to negative publicity based on the survey responses including open-ended feedbacks.
Sanitation of Canteen	Lack of evidence of association with negative publicity	Negative headlines occurred even when workers faced no sanitation issues related to canteens inside factories.

Table 4.15 Conclusion and the key takeaways from both research objectives (Continued)		
Variables	**Conclusion**	**Key Takeaways**
Forced Overtime	Evidence of an association with negative publicity	Forced overtime inside an apparel factory can lead to negative publicity based on the survey responses including open-ended feedbacks and news sources findings.
FOA	Evidence of an association between FOA rights violation inside apparel factory and negative publicity	Long working hours with no breaks inside an apparel factory can lead to negative publicity based on the survey responses including open-ended feedbacks.
Clean Water	Lack of evidence of association between clean water accessibility inside an apparel factory and negative publicity	Negative headlines occurred even when workers did not face clean water accessibility issues. So, clean water has no evidence of association with negative publicity.
Buyer-Supplier Relationship	Evidence of an association between strong buyer-supplier relationship and the absence of negative publicity	When suppliers are visible to the brands, and brands do know or have information about where their product is manufactured, then factories using visible contractors (i.e., tier1 and tier2 supplier) may lead to absence of negative publicity.

Table 4.15 Conclusion and the key takeaways from both research objectives (Continued)		
Variables	**Conclusion**	**Key Takeaways**
Cooperative Inspection	Evidence of an association between announced feedback crowdsourcing and the absence of negative publicity	An announced approach to feedback crowdsourcing is a potential indicator of the absence of negative publicity because an announced approach involves the joint problem solving including both suppliers and brands to address workplace issues and to prevent reputation spill overs.
Certification	Lack of evidence of an association between certified apparel factories and negative publicity	The majority of negative headlines showed up in the factories that were not certified by either WRAP, SA 8000, or WRC. So, lack of certification may be a good indicator that factories will receive negative publicity. But since there was a contradiction in the findings between bootstrap stepwise logistic and exact logistic regression, we concluded that there is no association between certified apparel factories and negative publicity.

Table 4.15 Conclusion and the key takeaways from both research objectives (Continued)		
Variables	**Conclusion**	**Key Takeaways**
Open-ended Feedback	Forced overtime, FOA, Long working hours, and Sanitation of toilets were the only issues mentioned by workers from factories with negative publicity that were consistent with the findings from research objective 1.	The frequent triggering factors mentioned in negative news articles (see Appendix C) included the fire safety concerns, low wages, and forced overtime. Forced overtime was the only factory characteristics, which is consistent with the findings from both research objectives. Surprisingly, fire safety, the dominant triggering factor of negative publicity, was not in the findings of either of the analysis. Low wages were not included by XYZ in the feedback crowdsourcing survey but delay in wages. Low wages were mentioned by workers in the open-ended responses among factories receiving negative publicity and it was also the second most frequent triggering factor of negative publicity as mentioned in Appendix C. This overlap of triggering factors provides more legitimacy to the importance of providing workers a platform to express grievances.

Chapter 5: Results, Discussion, Conclusion, Implications, and Future Research

This dissertation is the first empirical attempt that used workers feedback crowdsourcing to limit reputational damage for apparel factories. This was accomplished by investigating the association between worker complaints and negative publicity received by apparel factories. Factories receiving negative publicity were further investigated to determine whether there was any pattern of worker issues. This chapter includes a summary of the results, a discussion of the analysis done in the previous section, and a conclusion with implications of the findings for both managers and researchers. The chapter also includes the limitations of this dissertation and discusses some of the promising areas that still need to be investigated in the future.

5.1 Result

In this section, the result of each of the research objectives including sub objective is summarized, based on the data analysis findings of Chapter 4.

Research Objective 1:

RO1a: To determine whether the type of publicity is associated with workers voluntarily providing feedback.

The statistical analysis did not provide any evidence about the association between workers' willingness to participate in a voluntary open-ended survey question about an apparel factory and negative publicity.

RO1b: To determine whether delay in wages are related to negative publicity.

The statistical analysis did not provide any evidence about the association between a delay in wages in an apparel factory and negative publicity.

RO1c: To determine whether fire safety violations are associated with negative publicity.

The statistical analysis did not provide any evidence about the association between fire safety violations in an apparel factory and negative publicity.

RO1d: To determine the relationship between the level of sanitation (both for toilets and canteen) and the type of publicity.

The statistical analysis did not provide any evidence about the association between poor sanitation conditions of canteen and toilets and negative publicity

RO1e: To determine whether workplace abuse is associated with negative publicity.

The statistical analysis did not provide any evidence about the association between abusive working conditions and negative publicity.

RO1f: To determine whether child labor is related to negative publicity

The statistical analysis did not provide any evidence about the association between child labor presence inside an apparel factory and negative publicity.

RO1g: To determine the relationship between worker recommendation and type of publicity.

The statistical analysis did not provide any evidence about the association between worker recommendation and negative publicity.

RO1h: To determine whether the type of publicity is associated with long working hours.

The statistical analysis did provide evidence about the association between long working hours in an apparel factory and negative publicity.

RO1i: To determine whether forced overtime is associated with negative publicity.

The statistical analysis did provide evidence about the association between forced overtime inside an apparel factory and negative publicity.

RO1j: To determine whether FOA rights violation is associated with negative publicity.

The statistical analysis did provide evidence about the association between FOA rights violation inside apparel factory and negative publicity.

RO1k: To determine whether clean water is associated with the absence of negative publicity.

The statistical analysis did not provide any evidence about the association between clean water accessibility inside an apparel factory and negative publicity.

RO1l: To determine the relationship between the type of brand-supplier relationship and type of publicity.

The statistical analysis did provide evidence about the association between strong buyer-supplier relationship and the absence of negative publicity.

RO1m: To determine the cooperative inspection approach associated with negative publicity.

The statistical analysis did provide evidence about the association between announced feedback crowdsourcing and the absence of negative publicity.

RO1n: To determine the certification status associated with negative publicity.

The statistical analysis did not provide any evidence about the association between certified apparel factories and negative publicity.

Research Objective 2:

RO2: To identify the differences between apparel factories with and without negative publicity.

Delay in wages, forced overtime, verbal abuse, physical abuse, FOA, long working hours, clean water accessibility, child labor, and sanitation of toilets were the issues faced by workers, based on open-ended response among factories receiving negative publicity. Wages, sanitation of toilet, worker recommendation, and forced overtime were the issues that were significantly different between negative and non-negative factories based on the findings of the Wilcoxon test.

5.2 Discussion

This dissertation discloses insights from comprehensive feedback analysis. The logistic regression analysis for the first research objective reveals that there is a positive association between some of the factory characteristics (i.e., forced overtime, FOA, and long working hours) and negative publicity about apparel factories. This analysis also reveals the negative association between some other factory characteristics (i.e., buyer-supplier relationship and cooperative approach to inspection) and negative publicity. The worker responses charts identified the pattern of worker responses, which showed some relevance to negative publicity, among factories receiving negative publicity. This includes wages, sanitation of toilet, worker recommendation, and forced overtime.

Open-ended workers feedback highlighted more issues than the collective pre-recorded survey attempts by workers, as seen in Table 5.1. This could happen because of several reasons. First, workers may have responded to surveys under factory management influence to favour factory management (i.e., survey responses on delay in wages among factories receiving negative publicity were satisfactory compare to the open-ended responses) as mentioned by workers in two factories receiving negative publicity, as can be seen in Table 4.14. Second, workers who answered the open-ended question gave negative feedback. This could happen because of the workers' personal conflict with either their supervisor or factory manager, the influence of the workers' unions, or the workers only responded to open-ended questions when they had grievances.

Table 5.1

Outcome of RO1 VS RO2

RO1 outcome	RO2 outcome	Triggering factors of negative publicity in negative news articles
Forced overtime, FOA, Long working hours	The Wilcoxon test findings were that there were significant differences between factories with negative headlines and those without on Delay in wages, Sanitation of toilets, Worker recommendation, and Forced overtime. Issues frequency findings: Delay in wages, Forced overtime, No complaints, Verbal abuse, Physical abuse, FOA, Long working hours, Clean water accessibility, Child labor, Sanitation of toilets, Inspection influenced by factory management.	Fire safety concerns, Low wages, Forced overtime, pay hike, layoff

The frequent triggering factors mentioned in negative news articles (see Appendix C) included the fire safety concerns, low wages, and forced overtime. Forced overtime was the only factory characteristics, which is consistent with the findings from both research objectives and news sources publications as presented in Table 5.1. Fire safety, the dominant triggering factor of negative publicity, was not in the findings of either of the analyses as mentioned in Table 5.1. The issues of low wages were not included by XYZ in the feedback crowdsourcing survey but

delay in wages under the variable ‘Wages’. Low wages were mentioned by workers in the open-ended responses among factories receiving negative publicity and was also the second most frequent triggering factor of negative publicity as mentioned in the details about negative factories in Appendix C. This mismatch of some of the workers issues (i.e., low wages, fire safety) between issues identified by workers and issues published by news media and an overlap of triggering factor (i.e., forced labor) across closed ended survey questions, open ended questions and news media publications provides more legitimacy to the importance of providing workers a platform to express grievances to get more layers of information and to eventually address workplace issues to control reputational spill over. The majority of the negative news articles occurred in the month of December as can be seen in Appendix C. This might have happened because of the rise in the number of working hours mandated by factory management to meet seasonal demands (i.e., black Friday, Thanksgiving, and New Year) from apparel brands. The number of negative news articles with a factory name mentioned were 12, followed by 9 negative news articles with a group name mentioned. So, the group name is as critical as the factory name when searching for negative news articles.

The Cooperative approach to inspection and buyer supplier relationships were the factory-level indicators that were consistent with the findings of previous studies, based on the factory audit reports. Distelhorst et al. (2016) conducted a study on more than 300 Nike factories across 11 countries using audit reports and found that their strong buyer-supplier relationship helped Nike to reduce code violations by 15 percent. This finding is consistent with the findings from this dissertation where factories with strong buyer-supplier relationships led to the absence of negative publicity.

The Cooperative approach to feedback crowdsourcing led to the absence of negative publicity as joint problem solving is more effective in addressing workplace issues. This finding is consistent with the findings of Locke et al. (2009) where scholars used factory audit data. The study concluded that joint problem solving helped a Honduras based apparel supplier to decrease efficiency drops from 20 percent to just 4 percent which also helped to address workplace grievances. The study from Hugill et al. (2016) found that suppliers are more likely to improve when their auditors are highly trained and when the monitoring is done in cooperative arrangement. These consistent findings from different studies using factory audits reports and worker feedback crowdsourcing is convincing evidence that the feedback crowdsourcing can be used in addition to factory audit reports to address workplace grievances. It could provide the basis for the identification of factory-level indicators that can overlap, based on both factory audits and workers feedback crowdsourcing.

Worker feedback crowdsourcing seems to be a better data source compared to factory audits reports in disclosing FOA violations. This is backed by numerous studies that identified the inability of factory audits to detect FOA violations (Anner, 2012, Egels-Zandén et al., 2015, O'Rourke 2000). For Example, Anner (2012) conducted an empirical study that analysed 805 factory audit reports published by the Fair Labor Association from 2002 to 2010. He found that factory audits detected only a 5 percent FOA violation rate (despite FLA's strong emphasis on the detection of FOA violations), compared to a 40 percent violation detection in workplace safety and 30 percent detection in low wages. Anner (2012) concluded that lack of FOA detection is the result of FLA's inadequate factory audit process.

Forced overtime, long working hours, and sanitation of toilets are the factory characteristics that showed a significant association with the negative publicity of apparel

factories. The findings from these factory characteristics are consistent with previous studies where these issues contributed to job dissatisfaction and are more likely to cause unrest on the factory floor (Islam et al., 2012, Yu, 2008, Tiotangco et al., 2012, Domoney, 2007).

This dissertation presented some insights which are new and not substantiated by any of the previous studies since this is the first empirical study regarding workers feedback crowdsourcing. Workers feedback crowdsourcing failed to capture fire safety issues. Workers responses did not suggest that fire safety is a concern. There is a possibility that factory management already addressed safety issues and workers were already satisfied. If we assume this is true, then fire safety concerns should not be included in the list of most frequent triggering factors captured by news media sources in 2016 in Bangladesh. This clearly shows a disagreement between worker grievances in the workplace and the triggering factors that are captured in the media. However, there is slight agreement between the findings from both workers responses and news publication information where both were able to capture forced labor. These findings suggest a potential of utilising both worker crowdsourcing feedback and news media sources to investigate different layers of information and to protect the reputation of apparel factories.

5.3 Conclusion

This dissertation provides rich insights by presenting different layers of information that can be utilized to improve the living conditions of millions of factory workers in the global apparel supply chain. The layers of information presented and discussed in this dissertation included worker survey responses, open-ended worker responses, publicly available information about apparel factories, and the information captured from both local Bangladeshi and international news publishers. Each of them provided information about different factory characteristics.

Some of the factory characteristics were associated with negative publicity (i.e., forced overtime, FOA, long working hours, cooperative approach, buyer-supplier relationship) while others were not (i.e., abuse, child labor, clean water, sanitation of canteen). Some of the factory characteristics were consistent across different layers (i.e., forced overtime) while others were inconsistent (i.e., low wages, fire safety). The findings of some factory characteristics (i.e., buyer-supplier relationship, cooperative approach to inspection) from workers feedback crowdsourcing were consistent with the findings of previous studies from factory audit reports. In summary, this dissertation provided a case for the utilisation of a newly proposed data source and concluded that the workers feedback crowdsourcing data source is rich enough and can be utilized to address workplace issues to avoid negative publicity about apparel factories and associated apparel brands. This research will prove useful for existing factory audit reports.

5.4 Implication

This dissertation suggests intuitive implications for factory/sourcing/compliance/supply chain/corporate social responsibility managers, researchers, and XYZ which is discussed separately in the following section.

5.4.1 For Managers

This dissertation makes a case for managers from both factories and brands to consider workers feedback crowdsourcing as an additional data source to protect the respective organizations from reputational damage. The proposed data source can act as an additional layer of information about worker living conditions, in addition to existing alternatives (i.e., factory audits). The last three months of the year needs to be keenly observed as the majority of negative headlines occurred in the months of December and January potentially because of increase in work intensity.

5.4.2 For Researchers

This dissertation presents insights for researchers in the corporate sustainability or social responsibility domain. Researchers can use workers feedback crowdsourcing to investigate the proven factory indicators (as cooperative approach to inspection and buyer supplier relationship did in this dissertation) from earlier studies by using factory audits. For instance, Toffel (2015) found that female auditors were more likely to detect code violation than male auditors by analysing factory audits report. This means that the composition of audit teams based on gender impacts the monitoring of a supplier. Workers feedback crowdsourcing can also be split, based on survey-respondent gender and by determining whether gender plays a role in disclosing issues. Researchers can also use workers feedback crowdsourcing to investigate the mismatch between the triggering factors identified by workers and mainstream media. Our study shows that researchers should advocate for the proposed new data source to increase the number of studies involving workers feedback crowdsourcing.

5.4.3 For XYZ

This dissertation provides deep insights on various aspects of the worker feedback crowdsourcing platform that can help the workers feedback service provider (i.e., labor voices, labor links) to enhance the process of data collection and validation. This includes but is not limited to the inclusion of relevant issues in survey questionnaires, validation of workers survey responses and a mechanism to reduce factory management influence on survey responses. Based on the empirical findings of this dissertation, there are four areas that need more improvement. First, XYZ needs to ensure that the most relevant survey questions with the right scope are included in the survey. For example, the question of wages was included in the survey with the scope of delay in wages, but low wages were not included in the scope. Low wages were

identified by some workers using open-ended responses and is also one of the most triggering factors of negative publicity based on news media sources. So, open-ended feedback can be an effective way to keep track of newly identified issues that may need a separate survey question. Second, workers from two factories with negative publicity indicated the presence of factory management influence on survey responses which poses a bigger threat to the authenticity of the information provided by feedback crowdsourcing. Open-ended feedback proved to be a significant extra layer of information to disclose the presence of factory management influence. Open-ended feedback can potentially be used to validate the issues identified by other survey questions as shown in this dissertation. Third, worker responses in the last three months of the year needs to be keenly observed as the majority of negative headlines occurred in the months of December and January potentially because of increase in work intensity. Finally, local media sources can be used as an external validation data source to ensure a frequent cross check if the issues identified by workers are consistent with the ones mentioned by the local media sources.

5.5 Limitations

Though this dissertation is the first empirical study on workers feedback crowdsourcing producing significant results, this dissertation has some limitations:

1- The scope of this dissertation is on the apparel factory only. This means that the findings of this dissertation cannot be generalized to other manufacturing sectors.

2- The sample of this dissertation is selected from Bangladesh only, because of the availability of workers feedback crowdsourcing data. Therefore, country-related factors were not included in this dissertation.

3- This dissertation identified some of the gaps offered by factory audit reports but did not include factory audits because of the unavailability of audit reports for the sample

factories. Therefore, the proposed data source cannot be posed as a replacement for a factory audit.

4- Only 194 apparel factories were selected out of 5,000 in Bangladesh. This response rate is due to the workplace feedback system only being employed by 400 factories.

5- A local newspaper in the Bengali language was not included while searching negative headlines around sample factories. Therefore, the number of negative headlines during 2016 used in this dissertation may not be a true reflection of the number of negative headlines that occurred in Bangladesh.

6- Brand names were not searched while searching negative headlines because of the difficulty of tracing the exact factory name from the brand supply base.

7- All factories included in the group name (i.e., mentioned in negative news article published by media) were considered factories receiving negative publicity. There is a possibility that the group includes a factory that has nothing to do with the negative publicity published in the media. So, treating all factories as factories receiving negative publicity that were owned by a group name with a negative reputation may treat factories not receiving negative publicity as factories receiving negative publicity.

5.6 Future research

This dissertation sets the foundation for many other studies in the domain of monitoring the global apparel supply chain, potentially contributing to the body of knowledge in this area. Areas that reflect enormous potential for future research are discussed below:

1- An empirical study involving both factory audit reports and workers feedback crowdsourcing, to investigate whether the findings from these data sources compliment or contradict each other. This will require an overlap of good number of factories that

contain both worker feedback crowdsourcing and factory audit reports within the specific timeline. This research will provide the baseline settings for utilising both data sources to inspect suppliers' adherence to codes of conduct, in order to prevent brands' reputational damage.

2- This dissertation highlights the potential influence of factory management on survey responses. It will be interesting to investigate under which conditions factory management influences survey responses, and to posit mechanisms for minimizing that influence.

3- The apparel industry is cost-competitive. Any additional costs of extra measures to protect apparel factories' reputations may undermine the motivation of apparel brands to address labor disputes. It will be interesting to conduct a cost comparison study between factory audit and workers feedback crowdsourcing to see which data sources offer more cost-competitive and information-intensive information about apparel factory working conditions.

4- With the inclusion of workers feedback crowdsourcing as an additional data source option for monitoring supplier factories, there is a definitive need of theory-building that can put worker voices at the core of monitoring system, along with existing factory audit procedures. The extension of the existing factory audit practices model proposed by Prof. Richard Locke (2009) will be a good start.

5- This dissertation highlights the mismatch between triggering factors presented by local and mainstream media, and those identified by factory workers, using feedback crowdsourcing. A study that can address this mismatch between workers grievances and

triggers of negative publicity published by news media sources for same factories will be interesting to investigate to understand the potential causes of the mismatch.

REFERENCES

Absar, S. S. (2001). Problems surrounding wages: the ready made garments sector in Bangladesh. *Labor Management in Development*.

Acuna, E., & Rodriguez, C. (2004). The treatment of missing values and its effect on classifier accuracy. *Classification, clustering, and data mining applications*, 639-647.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE transactions on automatic control*, 19(6), 716-723.

Allison, P. D. (2012). *Logistic regression using SAS: Theory and application.* . Cary: SAS Institute.

Anisul Huq, F., Stevenson, M., & Zorzini, M. (2014). Social sustainability in developing country suppliers: An exploratory study in the ready made garments industry of Bangladesh. *International Journal of Operations & Production Management*, 34(5), 610-6.

Anner, M. (2012). Corporate social responsibility and freedom of association rights: The precarious quest for legitimacy and control in global supply chains . *Politics and Society*, 40(4), 609-644.

Anner, M., Bair, J., & Blasi, J. (2013). Toward joint liability in global supply chains: Addressing the root causes of labor violations in international subcontracting networks. *Comp. Lab. L. & Pol'y J*, 35, 1.

Ansary, M. A., & Barua, U. (2015). Workplace safety compliance of RMG industry in Bangladesh: Structural assessment of RMG factory buildings. . *International Journal of Disaster Risk Reduction,* , 14, 424-437.

Bartley, T. (2007). Institutional emergence in an era of globalization: The rise of transnational private regulation of labor and environmental conditions. . *American journal of sociology*, 113(2), 297- 351.

Bartley, T., & Child, C. (2014). Shaming the corporation: The social production of targets and the anti-sweatshop movement. . *American Sociological Review*, 79(4), 653-679.

Berik, G., & Rodgers, Y. V. (2010). Options for enforcing labour standards: Lessons from Bangladesh and Cambodia. . *Journal of International Development.The Journal of the Development Studies Association*, 22(1), 56-85.

Biggs, D., Ville, B. D., & Suen, E. (1991). A method of choosing multiway partitions for classification and decision trees. *Journal of Applied Statistics*, 18:1, 49-62.

Bloom, N., Genakos, C., Sadun, R., & Van Reenen, J. (2012). Management practices across firms and countries. *The Academy of Management Perspectives*, 26(1), 12-33.

Bouchery, Y., Corbett, C. J., Fransoo, J. C., & Tan, T. (2016). *Sustainable Supply Chains: A Research-based Textbook on Operations and Strategy (Vol. 4).* Springer.

Brown, A., Forde, C., Spencer, D., & Charlwood, A. (2008). Changes in HRM and job satisfaction, 1998–2004: evidence from the Workplace Employment Relations Survey. *Human Resource Management Journal*, 18(3), 237-256.

Brown, G. (2017). Hansae Vietnam's garment factory: Latest example of how corporate social responsibility has failed to protect workers. *Journal of Occupational and Environmental Hygiene.*

BSR. (2003). *Child Labour.* Business for Social Responsibility.

Chakraborty, G., Pagolu, M., & Garla, S. (2014). *Text mining and analysis: practical methods, examples, and case studies using SAS.* . SAS Institute.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16, 321-357.

Chen, C. H., & George, S. L. (1985). The bootstrap and identification of prognostic factors via Cox's proportional hazards regression model. *Statistics in medicine*, 4(1), 39-46.

Chen, L. &. (2016). Sourcing under supplier responsibility risk: The effects of certification, audit, and contingency payment. . *Management Science*.

Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory.* . Orlando : Holt, Rinehart and Winston.

Derksen, S., & Keselman, H. J. (1992). Backward, forward and stepwise automated subset selection algorithms: Frequency of obtaining authentic and noise variables. . *British Journal of Mathematical and Statistical Psychology*, 45(2), 265-282.

Distelhorst, G., Hainmueller, J., & Locke, R. M. (2016). *Does lean improve labor standards? Management and social performance in the Nike supply chain.* 63(3), 707-728: Management Science.

Domoney, R. (2007). *Briefing on the Chinese garment industry.* . Labour Behind the Label.

Du, W., & Zhan, Z. (2002). Building decision tree classifier on private data. *IEEE international conference on Privacy, security and data mining* (pp. 1-8). Australian Computer Society, Inc.

Efron, B., & Tibshirani, R. (1986). Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy. *Statistical science*, 54-75.

Egels-Zandén, N. &. (2015). Do codes of conduct improve worker rights in supply chains? A study of Fair Wear Foundation. *Journal of Cleaner Production*, 107, 31-40.

Farhana, K., Syduzzaman, M., & Munir, M. S. (2015). Present Status of Workers in Ready-Made Garments Industries in Bangladesh. *European Scientific Journal*, 11(7).

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, 56(4), 82-89.

Franzese, H., & Heuty, A. (2017, April 24). Unlocking worker voice using technology. (Sedex, Interviewer)

Frenkel, S. J., & Scott, D. (2002). Compliance, Collaboration, and Codes of Labor Practice: The" adidas" Connection. . *California Management Review*, 45(1), 29-49.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. (2006). Do alliances promote knowledge flows? . *Journal of Financial Economics*, , 80(1), 5-33.

Gorgemans, A. (2005). Addressing Child Labor: An Industry Approach. *eJournal USA*.

Harrell Jr, F. E. (2015). *Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis*.

Hernandez, E. (2014). Finding a home away from home: Effects of immigrants on firms' foreign location choice and performance. . *Administrative Science Quarterly*, 59(1), 73-108.

Hugill, A., Short, J. L., & Toffel, M. W. (2016). Beyond symbolic responses to private politics: examining labor standards improvement in global supply chains.

Improvement, F. I. (2017, November 15). *Factory Inspection And Improvement*. Retrieved from AEO: https://betterworld.ae.com/?page_id=87

Islam, M. A. (2010). Media pressures and corporate disclosure of social responsibility performance: a case study of two global clothing and sports retail companies. *Accounting and Business Research*.

Islam, M. K., & Zahid, D. (2012). Socioeconomic deprivation and garment worker movement in Bangladesh: A sociological analysis. *American Journal of Sociological Research*, 2(4), 82-89.

Islam, M. S. (2008). From sea to shrimp processing factories in Bangladesh: gender and employment at the bottom of a global commodity chain. *Journal of South Asian Development*, 3(2), 211-236.

Islam, M., Mustafi, M., & Islam, N. (2016). A Multivariate Analysis of Job Satisfaction of Ready-made Garments (RMG) Workers in Bangladesh.

Japkowicz, N. (2000). The class imbalance problem: Significance and strategies. . Int'l Conf. on Artificial Intelligence.

Jiang, B., Baker, R. C., & Frazier, G. V. (2009). An analysis of job dissatisfaction and turnover to reduce global supply chain risk: Evidence from China. *Journal of Operations Management*, 27(2), 169-184.

Kaptein, M. (2004). Business codes of multinational firms: What do they say? *Journal of Business Ethics*, 50(1), 13-31.

Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. *Applied statistics*, 119-127.

Keller, H. (2008). Codes of Conduct and their Implementation: the Question of Legitimacy. *In Legitimacy in International Law*, 219-298.

Kim, S. H., Carvalho, J. P., & Cooksey, C. E. (2007). Exploring the effects of negative publicity: News coverage and public perceptions of a university. *Public Relations Review, ,* 33(2), 233-235.

Kubat, M., & Matwin, S. (1997). Addressing the curse of imbalanced training sets: one-sided selection. *ICML*, 179-186.

Lahiri. (2012, December 24). *Can mobile phones improve factory safety?* Retrieved from Wall Street Journal: https://blogs.wsj.com/indiarealtime/2012/12/24/can-mobile-phones-improve-factory-fire-safety/

Larson, C. (2013). *China's Female Factory Workers Face Widespread Sexual Harassment.* China Labour Bulletin.

Locke, R. M., Qin, F., & Brause, A. (2007). Does monitoring improve labor standards? Lessons from Nike. *ILR Review*, 61(1), 3-31.

Locke, R. M., Rissing, B. A., & Pal, T. (2013). Complements or substitutes? Private codes, state regulation and the enforcement of labour standards in global supply chains. *British Journal of Industrial Relations*, 51(3), 519-552.

Locke, R., Amengual, M., & Mangla, A. (2009). Virtue out of necessity? Compliance, commitment, and the improvement of labor conditions in global supply chains. *Politics & Society*, 37(3), 319-351.

Lund-Thomsen, P., & Lindgreen, A. (2014). Corporate social responsibility in global value chains: Where are we now and where are we going? . *Journal of Business Ethics, ,* 123(1), 11-22.

Mamic, I. (2005). Managing global supply chain: the sports footwear, apparel and retail sectors. *Journal of business ethics*, 59(1-2), 81-100.

Martin, M. (2015). *Building the impact economy: Our future, yea or nay.* Springer.

Mayer, K. J., Nickerson, J. A., & Owan, H. (2004). Are supply and plant inspections complements or substitutes? A strategic and operational assessment of inspection practices in biotechnology. *Management Science*, 50(8), 1064-1081.

McAdam, D., & Su, Y. (2002). The war at home: Antiwar protests and congressional voting, 1965 to 1973. *American Sociological Review*, 696-721.

Miller, D., & Williams, P. (2009). What price a living wage? Implementation issues in the quest for decent wages in the global apparel sector. . *Global Social Policy*, 9(1), 99-125.

Moore, M., & Carpenter, J. M. (2010). A decision tree approach to modeling the private label apparel consumer. . *Marketing Intelligence & Planning,* , 28(1), 59-69.

Newlands, M. (2017, May 15). *supply-chain-transparency-and-the-tech-startups-creating-it-which-may-be-the-next-disruptor.* Retrieved from supply chain transparency and the tech startups: https://www.forbes.com/sites/mnewlands/2017/05/15/supply-chain-transparency-and-the-tech-startups-creating-it-which

Nickerson, J. A., & Silverman, B. S. (2003). Why aren't all truck drivers owner-operators? Asset ownership and the employment relation in interstate for-hire trucking. *Journal of Economics & Management Strategy*, 12(1), 91-118.

Noorani, S. (2007). *Child protection from violence, exploitation and abuse*. Retrieved from Unicef: https://www.unicef.org/protection/57929_58005.html

O'Rourke, D. (2000). *Monitoring the monitors: a critique of PricewaterhouseCoopers (PwC) Labor Monitoring. Department of Urban Studies and Planning Massachusetts Institute of Technology.* Boston: MIT.

O'Rourke, D. (2003). Outsourcing regulation: Analyzing nongovernmental systems of labor standards and monitoring. *Policy Studies Journal*, 31(1), 1-29.

policies, l. &. (2017, November 15). *labor & human rights policies.* Retrieved from Corporate Target: https://corporate.target.com/corporate-responsibility/responsible-sourcing/social-compliance/labor-and-human-rights

Pullig, C., Netemeyer, R. G., & Biswas, A. (2006). Attitude basis, certainty, and challenge alignment: A case of negative brand publicity. *Journal of the Academy of Marketing Science*, 34(4), 528-542.

Rahman, M. A., & Hossain, M. S. (2010). Compliance practices in garment industries in Dhaka city. *Journal of Business and Technology (Dhaka)*, 5(2), 71-87.

Rodríguez-Garavito, C. A. (2005). Global governance and labor rights: Codes of conduct and anti-sweatshop struggles in global apparel factories in Mexico and Guatemala. *Politics & Society*, 33(2), 203-333.

Sauerbrei, W., & Schumacher, M. (1992). A bootstrap resampling procedure for model building: application to the Cox regression model. *Statistics in medicine*, 11(16), 2093-2109.

Schwartz. (2013). Can mobile phones prevent more factory deaths? . Retrieved from Fast Company.

SCM. (2015). *http://www.scmworld.com/Charts-and-Infographics/*. Retrieved from http://www.scmworld.com/Charts-and-Infographics/

Short, J. L. (2010). Making self-regulation more than merely symbolic: The critical role of the legal environment. *Administrative Science Quarterly*, 55(3), 361-396.

Short, J. L., Toffel, M. W., & Hugill, A. R. (2016). Monitoring global supply chains. *Strategic Management Journal, 37(9),* 1878-1897.

Singh, V. K., Piryani, R. U., & Waila, P. (2013). Sentiment analysis of movie reviews: A new feature-based heuristic for aspect-level sentiment classification. In Automation. *computing, communication, control and compressed sensing*.

Sustainability, G. (2017, November 15). *improving factory working conditions*. Retrieved from Gap Sustainability: http://www.gapincsustainability.com/people/improving-factory-working-conditions/creating-better-data

Tiotangco, A., & Nunag, W. (2012). Sanitation. Hygiene, Health and Socio-economic Profiles of the Beneficiaries of the Far Eastern University (FEU) GawadKalinga (GK) Village Housing Project.

Toffel, M. W., Short, J. L., & Ouellet, M. (2015). Codes in context: How states, markets, and civil society shape adherence to global labor standards. *Regulation & Governance*, 9(3), 205-223.

Van Mieghem, J. A. (1999). Coordinating investment, production, and subcontracting. *Management Science*, 45(7), 954-971.

Vinodkumar, M. N., & Bhasi, M. (2011). A study on the impact of management system certification on safety management. *Safety science*, 49(3), 498-507.

Wadud, Z., Huda, F. Y., & Ahmed, N. U. (2014). Assessment of fire risk in the readymade garment industry in Dhaka, Bangladesh. *Fire Technology*, 50(5), 1127-1145.

Wan, X. (2008). Using bilingual knowledge and ensemble techniques for unsupervised Chinese sentiment analysis. . *empirical methods in natural language processing* (pp. 553-561). Association for Computational Linguistics.

Wilkinson, A., Donaghey, J., Dundon, T., & Freeman, R. B. (2014). *Handbook of Research on Employee Voice: Elgar original reference.* Edward Elgar Publishing.

Williamson, O. E. (1985). The economic institutions of capitalism.

Yu, X. (2008). Impacts of corporate code of conduct on labor standards: A case study of Reebok's athletic footwear supplier factory in China. . *Journal of Business Ethics*, 81(3), 513-529.

Yu, X. (2009). From passive beneficiary to active stakeholder: Workers' participation in CSR movement against labor abuses. . *Journal of Business Ethics*, 87, 233-249.

Zellner, D., Keller, F., & Zellner, G. E. (2004). Variable selection in logistic regression models. *Communications in Statistics-Simulation and Computation*, 33(3), 787-805.

APPENDICES

Appendix A

Code of Conduct Categories from Apparel Industry Audit Provider

Table A.1: Code of Conduct across Apparel Industry

Code of Conducts	Auditors						
	FLA	SAI	FWF	WRC	LV	Intertek	SGS
Nondiscrimination	1	1	1	1	0	1	1
Harassment or Abuse/ Disciplinary practices	1	1	0	1	1	1	1
Forced Labor	1	1	1	1	0	1	1
Child Labor	1	1	1	1	1	1	1
FOA/Collective Bargaining	1	1	1	1	0	0	1
Health, Safety and Environment	1	1	1	1	1	1	1
Hours of Work	1	1	1	1	1	1	1
Compensation/Remuneration	1	1	1	1	1	1	1
Employment Relationship	1	0	1	0	0	0	1
Management System	0	1	0	0	0	1	0
Overtime compensation	0	0	0	1	1	0	0
Women's Rights	0	0	0	1	0	0	0
Sanitation	0	0	0	0	1	0	0
Worker recommendation	0	0	0	0	1	0	0
Labor Contracts	0	0	0	0	0	1	0
Environment Management System	0	0	0	0	0	1	0
Life threatening condition	0	0	0	0	0	1	0
Bribery	0	0	0	0	0	1	0

Appendix B

List of References and Associated Keywords

Table B.1: List of References and Associated Keywords

Keyword	**Reference**
#sustainability, #manufacturing,#supplychain,#csr, #humanrights, #labour, #Bangladeshi, #slave, #ethics, #working conditions, #risk, #humanrights, #humantrafficking, #safety, #Bangladesh factory fires, #labor shortage, #risk management.	Chae, B. K. (2015). Insights from the hashtag# supply chain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research. *International Journal of Production Economics*, *165*, 247-259.
Fire, Safety, Child labor, Poor Ventilation, Poor lighting, forced overtime, abuse, forced overtime, malnutrition, deaths, injuries, Pregnant women, discrimination, locked doors, unpaid, Suppliers, Apparel Factory, workers, kill, Factory Fire, Inspector Certification, Exits locked, Garment workers, blaze, Subcontracting, Bangladesh factory, Building Collapse	Peterson, E. (2016). *Hazards, negligence, and abuse in the apparel manufacturing industry: Labor conditions from 1910-2015* (Doctoral dissertation, Kent State University).

Table B.1: List of References and Associated Keywords (Continued)	
Keyword	**Reference**
Protest, Factory disasters	Social Set Analysis: Four Demonstrative Case Studies
Child, Bangladesh, clothing, concerns, disclosure, environmental, factory, issues, labor, social, garments, human	Azizul Islam, M., & Deegan, C. (2008). Motivations for an organization within a developing country to report social responsibility information: Evidence from Bangladesh. *Accounting, Auditing & Accountability Journal*, *21*(6), 850-874.
Factories, issues, labor, overtime, workers, conditions, compliance, wages	Locke, R. M., & Romis, M. (2007). Improving work conditions in a global supply chain. *MIT Sloan Management Review*, *48*(2), 54.
Compliance, factory, labor, working condition, workers, over time, human, rights	Locke, R., Amengual, M., & Mangla, A. (2009). Virtue out of necessity? Compliance, commitment, and the improvement of labor conditions in global supply chains. *Politics & Society*, *37*(3), 319-351.
Labor, workers, strikes, disputes, union, resistance, wages, work	Kan Wang, (2016),"Labour resistance and worker attitudes towards trade union reform in China", Employee Relations, Vol. 38 Iss 5 pp. 724 – 740

Table B.1: List of References and Associated Keywords (Continued)	
Keyword	**Reference**
Apparel, Bangladesh, conditions, labor, rights, workers, factories, fire, wages, poor, addressing	Ahmed, N., & Peerlings, J. H. (2009). Addressing workers' rights in the textile and apparel industries: Consequences for the Bangladesh economy. *World Development*, *37*(3), 661-675.
Rights, RMG, Bangladesh, human, factories, workers, labor, disaster, garment, issues, owners	Javed Siddiqui Shahzad Uddin, (2016),"Human rights disasters, corporate accountability and the state", Accounting, Auditing & Accountability Journal, Vol. 29 Iss 4 pp. 679 – 704
Human, Rights, garment, labor, reporting, disclosure	Islam, M. A., & McPhail, K. (2011). Regulating for corporate human rights abuses: The emergence of corporate reporting on the ILO's human rights standards within the global garment manufacturing and retail industry. *Critical Perspectives on Accounting*, *22*(8), 790-810.
Accidents, Bangladesh, garments, Textile	Parvin, N., Prova, A. A., & Tabassum, M. (2015). Comparative Analysis of Industrial Mishaps Based on Classified Prediction.

Table B.1: List of References and Associated Keywords (Continued)	
Keyword	**Reference**
Apparel, car, textiles, social	Gaskill-Fox, J., Hyllegard, K. H., & Ogle, J. P. (2014). CSR reporting on apparel companies' websites: framing good deeds and clarifying missteps. *Fashion and Textiles*, *1*(1), 11.
Audit, Bangladesh, codes, condition, factory, garments, labor, workers, issues, NGOs	Islam, M. A., Deegan, C., & Gray, R. (2015). Social audits and multinational company supply chain: A study of rituals of social audits in the Bangladesh garment industry.
Bangladesh, factory, clothes, collapse, violations, workers, labor, garments	Padmanabhan, V. M., Baumann-Pauly, D., & Labowitz, S. (2015). The Hidden Price of Low Cost: Subcontracting in Bangladesh's Garment Industry.
Accord, Alliance, Bangladesh, factories, garment, Dhaka, rights, safety, workers, suppliers	Report: Beyond the Tip of the Iceberg: Bangladesh's Forgotten Apparel Workers
Child, Factories, labor, forced, minimum, rights, working, wages, abuses, conditions, companies, audit, clothing, issues, contract, suppliers, workers	Nike pilot project

Appendix C

Details about Negative Factories

Table C.1: Details about Negative Factories

Title	**Fac_ID**	**Date of Event**	**Trigger of Event**	**Outcome**
Ashulia apparel factories resume work after five days	A190, A69	26-Dec	layoff, low wage	protest
Bangladesh Accord cuts ties with four more factories	A9	24-Feb	lack of fire safety	accord cut ties
Fire at knitwear factory in Gazipur, 2 hurt	A45	9-Dec	fire	2 injured
Fire at RMG factory in Ashulia	A116	19-Nov, Dec 25	Fire, low wage	no injury, strike
Fire panic leaves 50 RMG workers hurt in Gazipur	A36	12-Dec	fire	50 injured
Suspended by Accord (information gathered from accord website), Global Retailers Call for Action on Labor Issues in Bangladesh	A56	Aug-16, Jan 20,2017	lack of fire safety, Forced Overtime	accord cut ties
Suspended by Accord (information gathered from accord website)	A132	Oct-16	lack of fire safety	accord cut ties

Table C.1: Details about Negative Factories (Continued)				
Title	**Fac_ID**	**Date of Event**	**Trigger of Event**	**Outcome**
Suspended by Accord (information gathered from accord website)	A150	Dec-16	lack of fire safety	accord cut ties
Inspection report from FLA	A102	Oct- 23	Violation in codes	
Rana Plaza tragedy marks 3rd anniversary	A11	April 23	demand for the mourning day for Rana plaza event	Protest on street
Bangladesh Canvas: AFWA levels allegations on Walmart's Bangladesh suppliers	A14	Aug 1	Report of illegal overtime by Asia Floor Wage Alliance (AFWA)	Wage and Overtime limit issues
Stories from Slate; Three-and-a-half years after a deadly collapse, Bangladesh's apparel factories have safer structures-and working conditions so oppressive they're killing people.	A27	Dec 15	Unsafe working condition, low wage	Workers view in a news article

Table C.1: Details about Negative Factories (Continued)				
Title	**Fac_ID**	**Date of Event**	**Trigger of Event**	**Outcome**
Global news roundup	A65	Nov 15	Lack of fire exit, low wages	
Bangladesh Accord cuts ties with Young International	A192	June 6	Lack of fire safety	Suspension from Accord
Remediations and suspensions for Bangladesh Alliance	A22	Jan 10, 2017	Remediation process completed	Considered as safe facility
Two more Bangladesh Alliance factories fully remediated	A30	Jun 14	Remediation process completed	Considered as safe facility
January 22, 2017: Gestion Credit Expert Sarl; News Media, Target of Trump's Declaration of War, Expresses Alarm	A26	Jab 23, 2017	Low wage	Worker view in a report
Labour unrest-hit Bangladesh factories reopen	A126	27-Dec	wage hike	strike
News Track: Bangladesh: Accord and Alliance show door to six more RMG factories	A142	Oct 13	suspended by accord	Accord cuts ties

Table C.1: Details about Negative Factories (Continued)				
Title	**Fac_ID**	**Date of Event**	**Trigger of Event**	**Outcome**
Protests in Bangladesh Shake a Global Workshop for Apparel	A157	Jan 22, 2017	low wage	Strike
Global Retailers Call for Action on Labor Issues in Bangladesh	A163	20-Jan	workers suspension	strike
Ashulia apparel factories resume work after five days	A19	26-Dec	strike for pay hike	strike
Ashulia apparel factories resume work after five days	A23	26-Dec	strike for pay hike	strike
Ashulia apparel factories resume work after five days	A137	26-Dec	strike for pay hike	strike
Ashulia apparel factories resume work after five days	A174	26-Dec	strike for pay hike	strike
Ashulia RMG factories reopened	59 Factories	26-Dec	Pay hike	strike

Appendix D

Python Code for Data Pre-processing

Table D.1: Python Code for Data Pre-processing

```
"""Objective: To perform the data pre-processing to prepare the data for analysis

Packages: Numpy, Pandas, OS, Matplotlib, Seaborn """

# Set your working directory with os.chdir()

# importing packages required for manipulating the data

import os

import pandas as pd

import numpy as np

import matplotlib as mlt

import seaborn as sn

os.chdir("C:\\Users\\Hammad\\Desktop\\Maaz")

# Created a for loop to read all 194 excel files and append them by using append() function in a

data frame called "data". There were 22290 rows and 294 columns in the data frame "data". Then

the names of column were saved in the list "names" to keep track of an index. There were 294

columns name in the list "names"

data=pd.DataFrame()

for i in range(1,195):

    st= str("a")+str(i)+str(".xlsx")

    temp=pd.read_excel(st)

    data=data.append(temp)

names=list(data.columns.values)
```

In the next step, Only the relevant columns were save in the list "id" using column index in the data frame named "df1" containing 22290 rows and 31 columns

```
id=[30,266,26,29,57,58,59,60,61,68,76,77,78,79,80,81,82,267,268,269,270,271,278,286,287,288
,289,290,291,292]
nm=[]
for i in range(0,len(id)):
    nm.append(names[id[i]])
df1=data[nm]
```

Index was reset. Remember we append 194 files in one data frame. This repeated every index number 194 times. To fix this "reset_index" was used.

```
test=df1.reset_index()
df1=test.drop('index',axis=1)
```

In the next step, we merged all 13 questions and 13 answers column in one respective columns respectively. In the original data frame, the questions were mixed in each question columns so as answers in each answer column. So we first need to merge all questions and their answers in one column so that we can sort the questions and make a separate column for each of them. To do this we need to maintain unique identifiers that can track the records based on responses by unique workers in each factory. So we had "fac_id" as factory identifiers and "user_id" as user identifier along with duration of the call and timestamps. Each page_name column represent a question in the survey and user_input represent the answer. There were 13 questions and their respective answers. So, we merged page_name-1 to page_name-13 into one column "questions" and so as user_input-1 to user_input-13 into one column "answers" by using "concat". The code for page_name is below:

```
dataframe1=df1[nm[0:5]]
cn=[]
cn=nm[0:3]
cn.append(nm[5])
dataframe2=df1[cn]
dataframe2=dataframe2.rename(columns={'page_name-10': 'page_name-1'})
new=pd.concat([dataframe1,dataframe2])
for i in range(6,17):
    cn=[]
    cn=nm[0:3]
    cn.append(nm[i])
    dataframe2=df1[cn]
    dataframe2=dataframe2.rename(columns={nm[i]: 'page_name-1'})
    new=pd.concat([new,dataframe2])
# the code for user_input is:
cn=nm[0:4]
cn.append(nm[17])
dataframe1=df1[cn]
for i in range(18,30):
    cn=nm[0:4]
    cn.append(nm[i])
    dataframe2=df1[cn]
    dataframe2=dataframe2.rename(columns={nm[i]: 'user_input-1'})
```

```
    dataframe1=pd.concat([dataframe1,dataframe2])
dataframe1['questions']=new['page_name-1']
dataframe1['answers']=new['user_input-1']
# Now the sorting is done based on questions
dataframe1=dataframe1.sort_values(by=['questions'])
```

Next we created a new column "Version" which splits the rows based on timestamps into 1 & 2. The survey was updated 2 times in the year 2016 and each survey contains different questions. Version 1 is responses from Jan to Aug, and Version 2 is from Sept to Dec. Version column is created by creating test_func:

```
def test_func(df):
    """ Test Function for generating new value"""
    if int(df['conversation_created_at'][5:8]) <=8:
        return 1
    else:
        return 2
dataframe1["version"] = dataframe1.apply(test_func,axis=1)
# The file was exported to the desired folder
from pandas import ExcelWriter
writer = ExcelWriter('Hammadfinal.xlsx')
dataframe1.to_excel(writer,'Sheet5')
writer.save()
```

Appendix E

SAS code for response frequencies

Table E.1: SAS code for response frequencies

```
libname hammad 'C:\Users\mhabbasi\Desktop\hammad';

proc import datafile="C:\Users\mhabbasi\Desktop\hammad\Hammadfinal2.xlsx"

out=Hammadfinal;

run;

proc import datafile="C:\Users\mhabbasi\Desktop\hammad\Hammadfinal23.xlsx"

out=Hammadfinal23;

run;

proc sort data=hammadfinal;

by fac_id;

run;

proc means data=hammadfinal n mean;

var duration Sanitation_Canteen Sanitation_toilet;

class fac_id;

output out =v12 mean= mean_duration mean_Sanitation_Canteen mean_Sanitation_toilet;

run;

proc freq data=hammadfinal;

tables fac_id*Fire_Exits / noprint Out= freq1;

run;

proc freq data=hammadfinal;

by fac_id;
```

```
tables fac_id*Feedback / noprint Out= freq2;

run;

proc freq data=hammadfinal;

by fac_id;

tables fac_id*Long_Hours / noprint Out= freq3;

run;

proc freq data=hammadfinal;

by fac_id;

tables fac_id*abuse/ noprint Out= freq4;

run;

proc freq data=hammadfinal;

by fac_id;

tables fac_id*Child_Labor / noprint Out= freq5;

run;

proc freq data=hammadfinal;

by fac_id;

tables fac_id*Wages / noprint Out= freq6;

run;

proc freq data=hammadfinal;

by fac_id;

tables fac_id*Sanitation_Canteen / noprint Out= freq7;

run;

proc freq data=hammadfinal;
```

```
by fac_id;

tables fac_id*Sanitation_toilet / noprint  Out= freq8;

run;

proc freq data=hammadfinal;

by fac_id;

tables fac_id*Recommendation / noprint Out= freq9;

run;

proc sort data=Hammadfinal23;

by fac_id;

run;

proc means data=Hammadfinal23 n mean;

var duration;

class fac_id;

output out =v3 mean= mean_duration;

run;

proc freq data=hammadfinal23;

by fac_id;

tables fac_id*Forced_Labor / noprint Out= freqa;

run;

proc freq data=hammadfinal23;

by fac_id;

tables fac_id*FOA / noprint Out= freqb;

run;
```

```
proc freq data=hammadfinal23;

by fac_id;

tables fac_id*Clean_Water / noprint Out= freqc;

run;

Proc sort data= v12 out = hammad.v12;

by fac_id;

run;

Proc sort data= v3 out = hammad.v3;

by fac_id;

run;

proc export data=hammad.v12 outfile="C:\Users\mhabbasi\Desktop\hammad\v12.xlsx"

dbms=xlsx replace;

run;

proc export data=hammad.v3 outfile="C:\Users\mhabbasi\Desktop\hammad\v3.xlsx"

dbms=xlsx replace;

run;

Proc sort data= freq1 out = hammad.freq1;

by fac_id;

run;

Proc sort data= freq2 out = hammad.freq2;

by fac_id;

run;

Proc sort data= freq3 out = hammad.freq3;
```

```
by fac_id;
run;
Proc sort data= freq4 out = hammad.freq4;
by fac_id;
run;
Proc sort data= freq5 out = hammad.freq5;
by fac_id;
run;
Proc sort data= freq6 out = hammad.freq6;
by fac_id;
run;
Proc sort data= freq7 out = hammad.freq7;
by fac_id;
run;
Proc sort data= freq8 out = hammad.freq8;
by fac_id;
run;
Proc sort data= freq9 out = hammad.freq9;
by fac_id;
run;
proc export data=hammad.freq1 outfile="C:\Users\mhabbasi\Desktop\hammad\freq1.xlsx"
dbms=xlsx replace;
run;
```

```
proc export data=hammad.freq2 outfile="C:\Users\mhabbasi\Desktop\hammad\freq2.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freq3 outfile="C:\Users\mhabbasi\Desktop\hammad\freq3.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freq4 outfile="C:\Users\mhabbasi\Desktop\hammad\freq4.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freq5 outfile="C:\Users\mhabbasi\Desktop\hammad\freq5.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freq6 outfile="C:\Users\mhabbasi\Desktop\hammad\freq6.xlsx"
dbms=xlsx replace;
run;

proc export data=hammad.freq7 outfile="C:\Users\mhabbasi\Desktop\hammad\freq7.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freq8 outfile="C:\Users\mhabbasi\Desktop\hammad\freq8.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freq9 outfile="C:\Users\mhabbasi\Desktop\hammad\freq9.xlsx"
```

```
dbms=xlsx replace;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq1.xlsx"  out=freq1;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq2.xlsx"  out=freq2;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq3.xlsx"  out=freq3;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq4.xlsx"  out=freq4;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq5.xlsx"  out=freq5;
run;

proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq6.xlsx"  out=freq6;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq7.xlsx"  out=freq7;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq8.xlsx"  out=freq8;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freq9.xlsx"  out=freq9;
run;
data freqv12;
   merge freq1 - freq9;
```

```
    by fac_id;
run;
Proc sort data= freqa out = hammad.freqa;
by fac_id;
run;
Proc sort data= freqb out = hammad.freqb;
by fac_id;
run;
Proc sort data= freqc out = hammad.freqc;
by fac_id;
run;
proc export data=hammad.freqa outfile="C:\Users\mhabbasi\Desktop\hammad\freqa.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freqb outfile="C:\Users\mhabbasi\Desktop\hammad\freqb.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freqc outfile="C:\Users\mhabbasi\Desktop\hammad\freqc.xlsx"
dbms=xlsx replace;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freqa.xlsx"  out=freqa;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freqb.xlsx"  out=freqb;
```

```
run;
proc import datafile="C:\Users\mhabbasi\Desktop\hammad\freqc.xlsx"  out=freqc;
run;
data freqv3;
   merge freqa freqb freqc;
   by fac_id;
run;


Proc sort data= freqv12 out = hammad.freqv12;
by fac_id;
run;
Proc sort data= freqv3 out = hammad.freqv3;
by fac_id;
run;
proc export data=hammad.freqv12 outfile="C:\Users\mhabbasi\Desktop\hammad\freqv12.xlsx"
dbms=xlsx replace;
run;
proc export data=hammad.freqv3 outfile="C:\Users\mhabbasi\Desktop\hammad\freqcv3.xlsx"
dbms=xlsx replace;
run;
```

Appendix F

SAS code for stepwise and exact logistic regression

Table F.1: SAS code for stepwise and exact logistic regression

```
libname hammad 'C:\Users\Hammad\Desktop\new oversampl';

/* Importing all datasets into sas */

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod121.xlsx"  dbms = xlsx

out=mod121;

run;

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod122.xlsx"  dbms = xlsx

out=mod122;

run;

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod123.xlsx"  dbms = xlsx

out=mod123;

run;

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod124.xlsx"  dbms = xlsx

out=mod124;

run;

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod125.xlsx"  dbms = xlsx

out=mod125;

run;

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12.xlsx"  dbms = xlsx

out=mod12;

run;
```

```
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12lg1.xlsx"  dbms = xlsx
out=mod12lg1;
run;

proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12lg2.xlsx"  dbms = xlsx
out=mod12lg2;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12lg3.xlsx"  dbms = xlsx
out=mod12lg3;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12lg4.xlsx"  dbms = xlsx
out=mod12lg4;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12lg5.xlsx"  dbms = xlsx
out=mod12lg5;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\mod12lg.xlsx"  dbms = xlsx
out=mod12lg;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\v31.xlsx"  dbms = xlsx
out=v31;
run;
```

```
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\v32.xlsx"  dbms = xlsx
out=v32;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\v33.xlsx"  dbms = xlsx
out=v33;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\v34.xlsx"  dbms = xlsx
out=v34;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\v35.xlsx"  dbms = xlsx
out=v35;
run;
proc import datafile="C:\Users\Hammad\Desktop\new oversampl\v3.xlsx"  dbms = xlsx out=v3;
run;
/* stepwise regression for variable selection and then logistic regression with stepwise variable
selection and then logistic regression on selected variables from each sub-sampled data */
/* stepwise regression for variable selection */
proc reg data= mod121;
model headline= sanitation_toilet -- fire/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod122;
model headline= sanitation_toilet -- fire/
```

```
selection = stepwise vif tol collinoint;

run;

proc reg data= mod123;

model headline= sanitation_toilet -- fire/

selection = stepwise vif tol collinoint;

run;

proc reg data= mod124;

model headline= sanitation_toilet -- fire/

selection = stepwise vif tol collinoint;

run;

proc reg data= mod125;

model headline= sanitation_toilet -- fire/

selection = stepwise vif tol collinoint;

run;

proc reg data= mod12;

model headline= sanitation_toilet -- fire/

selection = stepwise vif tol collinoint;

run;

proc reg data= mod12lg1;

model headline= sanitation_canteen -- recommendation/

selection = stepwise vif tol collinoint;

run;

proc reg data= mod12lg2;
```

```
model headline= sanitation_canteen -- recommendation/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod12lg3;
model headline= sanitation_canteen -- recommendation/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod12lg4;
model headline= sanitation_canteen -- recommendation/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod12lg5;
model headline= sanitation_canteen -- recommendation/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod12lg;
model headline= sanitation_canteen -- recommendation/
selection = stepwise vif tol collinoint;
run;
proc reg data= v31;
model headline= forced_labor -- clean_water/
selection = stepwise vif tol collinoint;
run;
```

```
proc reg data= v32;
model headline= forced_labor -- clean_water/
selection = stepwise vif tol collinoint;
run;
proc reg data= v33;
model headline= forced_labor -- clean_water/
selection = stepwise vif tol collinoint;
run;
proc reg data= v34;
model headline= forced_labor -- clean_water/
selection = stepwise vif tol collinoint;
run;
proc reg data= v35;
model headline= forced_labor -- clean_water/
selection = stepwise vif tol collinoint;
run;
proc reg data= v3;
model headline= forced_labor -- clean_water/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod121;
model headline= buyer_supplier_relationship -- cooperative_approach/
selection = stepwise vif tol collinoint;
```

```
run;
proc reg data= mod122;
model headline= buyer_supplier_relationship -- cooperative_approach/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod123;
model headline= buyer_supplier_relationship -- cooperative_approach/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod124;
model headline= buyer_supplier_relationship -- cooperative_approach/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod125;
model headline= buyer_supplier_relationship -- cooperative_approach/
selection = stepwise vif tol collinoint;
run;
proc reg data= mod12;
model headline= buyer_supplier_relationship -- cooperative_approach/
selection = stepwise vif tol collinoint;
run;
/* Stepwise logistic regression with input from stepwise regression  */
proc logistic data = mod121;
```

```
model headline(event= "1") = sanitation_toilet/

selection = stepwise clodds=pl;

run;

proc logistic data = mod122;

model headline(event= "1") = sanitation_toilet/

selection = stepwise clodds=pl;

run;

proc logistic data = mod123;

model headline(event= "1") = sanitation_toilet/

selection = stepwise clodds=pl;

run;

proc logistic data = mod124;

model headline(event= "1") = sanitation_toilet child_labor/

selection = stepwise clodds=pl;

run;

proc logistic data = mod125;

model headline(event= "1") = feedback child_labor/

selection = stepwise clodds=pl;

run;

proc logistic data = mod12;

model headline(event= "1") = sanitation_toilet feedback child_labor/

selection = stepwise clodds=pl;

run;
```

```
proc logistic data = mod12lg1;
model headline(event= "1") = sanitation_canteen/
selection = stepwise clodds=pl;
run;
proc logistic data = mod12lg2;
model headline(event= "1") = recommendation/
selection = stepwise clodds=pl;
run;
proc logistic data = mod12lg3;
model headline(event= "1") =  sanitation_canteen/
selection = stepwise clodds=pl;
run;
proc logistic data = mod12lg4;
model headline(event= "1") = recommendation sanitation_canteen/
selection = stepwise clodds=pl;
run;
proc logistic data = mod12lg5;
model headline(event= "1") = recommendation sanitation_canteen/
selection = stepwise clodds=pl;
run;
proc logistic data = mod12lg;
model headline(event= "1") = recommendation/
selection = stepwise clodds=pl;
```

```
run;

proc logistic data = v31;

model headline(event= "1") = foa forced_labor clean_water/

selection = stepwise clodds=pl;

run;

proc logistic data = v32;

model headline(event= "1") = forced_labor clean_water/

selection = stepwise clodds=pl;

run;

proc logistic data = v33;

model headline(event= "1") = forced_labor/

selection = stepwise clodds=pl;

run;

proc logistic data = v35;

model headline(event= "1") = forced_labor/

selection = stepwise clodds=pl;

run;

proc logistic data = v3;

model headline(event= "1") = forced_labor/

selection = stepwise clodds=pl;

run;

proc logistic data = mod121;

model headline (event= "1") = certified cooperative_approach/
```

```
selection = stepwise clodds=pl;

run;

proc logistic data = mod122;

model headline(event= "1") = buyer_supplier_relationship cooperative_approach/

selection = stepwise clodds=pl;

run;

proc logistic data = mod123;

model headline(event= "1") = certified cooperative_approach/

selection = stepwise clodds=pl;

run;

proc logistic data = mod124;

model headline(event= "1") = certified/

selection = stepwise clodds=pl;

run;

proc logistic data = mod125;

model headline(event= "1") = certified buyer_supplier_relationship/

selection = stepwise clodds=pl;

run;

proc logistic data = mod12;

model headline(event= "1") = certified cooperative_approach buyer_supplier_relationship/

selection = stepwise clodds=pl;

run;

/* Stepwise logistic regression with exact conditional test */
```

```
proc logistic data= mod121;
model headline(event= "1") = sanitation_toilet;
exact sanitation_toilet/estimate;
run;
proc logistic data= mod122;
model headline(event= "1") = sanitation_toilet;
exact sanitation_toilet/estimate;
run;
proc logistic data= mod123;
model headline(event= "1") = sanitation_toilet;
exact sanitation_toilet/estimate;
run;
proc logistic data= mod124;
model headline(event= "1") = sanitation_toilet;
exact sanitation_toilet/estimate;
run;
proc logistic data= mod12;
model headline(event= "1") = sanitation_toilet;
exact sanitation_toilet/estimate;
run;
proc logistic data= mod12lg1;
model headline(event= "1") = sanitation_canteen;
exact sanitation_canteen/estimate;
```

```
run;
proc logistic data= mod12lg2;
model headline(event= "1") = recommendation;
exact recommendation/estimate;
run;
proc logistic data= mod12lg3;
model headline(event= "1") = recommendation;
exact recommendation/estimate;
run;
proc logistic data= mod12lg4;
model headline(event= "1") = recommendation;
exact recommendation/estimate;
run;
proc logistic data= mod12lg;
model headline(event= "1") = recommendation;
exact recommendation/estimate;
run;
proc logistic data= v31;
model headline(event= "1") = forced_labor;
exact forced_labor/estimate;
run;
proc logistic data= v32;
model headline(event= "1") = forced_labor clean_water;
```

```
exact forced_labor clean_water/estimate;

run;

proc logistic data= v33;

model headline(event= "1") = forced_labor;

exact forced_labor/estimate;

run;

proc logistic data= v35;

model headline(event= "1") = forced_labor;

exact forced_labor/estimate;

run;

proc logistic data= v3;

model headline(event= "1") = forced_labor;

exact forced_labor/estimate;

run;

proc logistic data= mod121;

model headline(event= "1") = certified cooperative_approach;

exact certified cooperative_approach/estimate;

run;

proc logistic data= mod122;

model headline(event= "1") = buyer_supplier_relationship cooperative_approach;

exact buyer_supplier_relationship cooperative_approach/estimate;

run;

proc logistic data= mod123;
```

```
model headline(event= "1") = certified cooperative_approach;

exact certified cooperative_approach/estimate;

run;

proc logistic data= mod125;

model headline(event= "1") = certified buyer_supplier_relationship;

exact certified buyer_supplier_relationship/estimate;

run;

proc logistic data= mod12;

model headline(event= "1") = certified cooperative_approach;

exact certified cooperative_approach/estimate;

run;
```

Appendix G

Base SAS code for bootstrap estimate using Stepwise logistic regression

Table G.1: Base SAS code for bootstrap estimate using stepwise logistic regression

```
 libname hammad 'C:/Users/mhabbasi/Desktop/head17';
/* Importing both negative and nonnegative factories datasets to sas*/
proc import datafile="C:\Users\mhabbasi\Desktop\head17\mod12pos.xlsx"  dbms = xlsx
out=mod12pos;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\head17\mod12neg.xlsx"    dbms = xlsx
out=mod12neg;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\head17\mod12lgpos.xlsx"  dbms = xlsx
out=mod12lgpos;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\head17\mod12lgneg.xlsx"  dbms = xlsx
out=mod12lgneg;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\head17\v3pos.xlsx"    dbms = xlsx out=v3pos;
run;
proc import datafile="C:\Users\mhabbasi\Desktop\head17\v3neg.xlsx"    dbms = xlsx
out=v3neg;
run;
```

```
/* bootstrapping to get 1000 samples, each sample contains almost 32 random non-negative
factories observation */
%let NumSamples = 1000;       /* number of bootstrap resamples */
/* 2. Generate many bootstrap samples */
proc surveyselect data=mod12pos NOPRINT seed=1
    out=Freqmod12(rename=(Replicate=SampleID))
            seed=2
    method=urs              /* resample with replacement */
   samprate=0.1893492            /* each bootstrap sample has N observations */
    /* OUTHITS                 option to suppress the frequency var */
          /*n = 32*/
    reps=&NumSamples;       /* generate NumSamples bootstrap resamples */
run;
/* Adding negative headlines to each bootstrap sample that contains 32 random non-negative
factories */
%macro AddingNegativeHeadlines(NumSamples=);
proc sql;                           /*Count before adding negative headlines*/
          select count(*)
          from freqmod12;
run;
%do i=1 %to &NumSamples;
data negative;
          set mod12neg;
```

```
        SampleID = &i;
run;
data freqmod12;
        set freqmod12 negative;
run;
%end;
proc sort data=freqmod12;
 by sampleId fac_id;
run;
proc sql;                           /*Count after adding negative headlines*/
        select count(*)
        from freqmod12;
run;
%mend;
%AddingNegativeHeadlines(NumSamples=&NumSamples);
/* bootstrapping to get 1000 samples, each sample contains almost 32 random non-negative
factories observation */
%let NumSamples = 1000;     /* number of bootstrap resamples */
/* 2. Generate many bootstrap samples */
proc surveyselect data=mod12lgpos NOPRINT seed=1
out=Freqmod12lg(rename=(Replicate=SampleID))
seed=2
method=urs          /* resample with replacement */
```

```
samprate=0.2019            /* each bootstrap sample has N observations */
reps=&NumSamples;       /* generate NumSamples bootstrap resamples */
run;
/* Adding negative headlines to each bootstrap sample that contains 32 random non-negative
factories */
%macro AddingNegativeHeadlines(NumSamples=);
proc sql;                          /*Count before adding negative headlines*/
        select count(*)
        from Freqmod12lg;
run;
%do i=1 %to &NumSamples;
data negative;
        set mod12lgneg;
        SampleID = &i;
run;
data Freqmod12lg;
        set Freqmod12lg negative;
run;
%end;
proc sort data=Freqmod12lg;
 by sampleId fac_id;
run;
proc sql;                              /*Count after adding negative headlines*/
```

```
        select count(*)
        from Freqmod12lg;
run;
%mend;
%AddingNegativeHeadlines(NumSamples=&NumSamples);
/* bootstrapping to get 1000 samples, each sample contains almost 32 random non-negative
factories observation */
%let NumSamples = 1000;      /* number of bootstrap resamples */
/* 2. Generate many bootstrap samples */
proc surveyselect data=v3pos NOPRINT seed=1
    out=Freqv3(rename=(Replicate=SampleID))
         seed=2
    method=urs            /* resample with replacement */
   samprate=0.205          /* each bootstrap sample has N observations */
    /* OUTHITS              option to suppress the frequency var */
        /*n = 32*/
    reps=&NumSamples;      /* generate NumSamples bootstrap resamples */
run;
/* Adding negative headlines to each bootstrap sample that contains 32 random non-negative
factories */
%macro AddingNegativeHeadlines(NumSamples=);
proc sql;                          /*Count before adding negative headlines*/
        select count(*)
```

```
        from Freqv3;
run;
%do i=1 %to &NumSamples;
data negative;
        set v3neg;
        SampleID = &i;
run;
data Freqv3;
        set Freqv3 negative;
run;
%end;
proc sort data=Freqv3;
 by sampleId fac_id;
run;
proc sql;                           /*Count after adding negative headlines*/
        select count(*)
        from Freqv3;
run;
%mend;
%AddingNegativeHeadlines(NumSamples=&NumSamples);
/* stepwise logistic regression to get the estimates of 1000 boostrap samples containing almost
32 non negative and 16 negative factories */
options nonotes;
```

```
proc logistic data=freqmod12 noprint outest=PE;
   by SampleId;
   model headline(Event='1') = sanitation_toilet -- cooperative_approach;
run;
options notes;
data sample;
set pe;
run;
proc means data=sample;  var sanitation_toilet -- cooperative_approach;  run; /* compute value
of the means of all categories on all boostrap samples*/
/* Frequency distribution of estimates on each category */
title "Bootstrap Distribution For Estimates";
%let fire_exits = 0.2256;
proc sgplot data=sample;
   histogram fire_exits;
 refline &fire_exits / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let feedback = -17.14;
proc sgplot data=sample;
   histogram feedback;
 refline &feedback / axis=x lineattrs=(color=red);
run;
```

```
title "Bootstrap Distribution For Estimates";
%let abuse = -1.408;
proc sgplot data=sample;
   histogram abuse;
 refline &abuse / axis=x lineattrs=(color=red);
run;

title "Bootstrap Distribution For Estimates";
%let child_labor = 12.291;
proc sgplot data=sample;
   histogram child_labor;
 refline &child_labor / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let wages = 0.9227;
proc sgplot data=sample;
   histogram wages;
 refline &wages / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let sanitation_toilet = 2.055;
proc sgplot data=sample;
   histogram sanitation_toilet;
```

```
 refline &sanitation_toilet / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let Buyer_supplier_Relationship = -1.958;
proc sgplot data=sample;
   histogram Buyer_supplier_Relationship;
 refline &Buyer_supplier_Relationship / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let certified = -2.213;
proc sgplot data=sample;
   histogram certified;
 refline &certified / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let Cooperative_Approach = 13.566;
proc sgplot data=sample;
   histogram Cooperative_Approach;
 refline &Cooperative_Approach / axis=x lineattrs=(color=red);
run;
Proc sort data= sample  nodup out= hammad.mod12;
by sampleid;
run;
```

```
proc export data=hammad.mod12 outfile="C:\Users\mhabbasi\Desktop\head16\bootmod12.xls"
dbms=xls replace;
run;
* stepwise logistic regression to get the estimates of 1000 boostrap samples containing almost 32
non negative and 16 negative factories */
options nonotes;
proc logistic data=freqmod12lg noprint outest=PE2;
   by SampleId;
   model headline(Event='1') = sanitation_canteen -- recommendation;
run;
options notes;
data sample2;
set pe2;
run;
proc means data=sample2;  var sanitation_canteen -- recommendation;  run; /* compute value of
the means of all categories on all boostrap samples*/
/* Frequency distribution of estimates on each category */
title "Bootstrap Distribution For Estimates";
%let sanitation_canteen = 0.135;
proc sgplot data=sample2;
   histogram sanitation_canteen;
 refline &sanitation_canteen / axis=x lineattrs=(color=red);
run;
```

```
title "Bootstrap Distribution For Estimates";
%let long_hours = 1.119;
proc sgplot data=sample2;
   histogram long_hours;
 refline &long_hours / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let recommendation = -4.852;
proc sgplot data=sample2;
   histogram recommendation;
 refline &recommendation / axis=x lineattrs=(color=red);
run;
* stepwise logistic regression to get the estimates of 1000 boostrap samples containing almost 32
non negative and 16 negative factories */
options nonotes;
proc logistic data=freqv3 noprint outest=PE5;
   by SampleId;
   model headline(Event='1') = Forced_Labor -- clean_water;
run;
options notes;
data sample5;
set pe5;
run;
```

```
proc means data=sample5;  var Forced_Labor -- clean_water;  run; /* compute value of the
means of all categories on all boostrap samples*/
/* Frequency distribution of estimates on each category */
title "Bootstrap Distribution For Estimates";
%let forced_labor = 3.812;
proc sgplot data=sample5;
   histogram forced_labor;
 refline &forced_labor / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let foa = 1.747;
proc sgplot data=sample5;
   histogram foa;
 refline &foa / axis=x lineattrs=(color=red);
run;
title "Bootstrap Distribution For Estimates";
%let clean_water = -4.828;
proc sgplot data=sample5;
   histogram clean_water;
 refline &clean_water / axis=x lineattrs=(color=red);
run;
```

Appendix H

Questions from Versions 1, and 2

Table H.1: Questions from Versions 1, and 2

Questions	**Version 1**	**Version 2**
1. In the last month, were all your wages, including overtime hours, paid on time?	Included	Included
2. On a scale of 0 to 4, how would you rate the cleanliness of the toilet in the last month?	Included	Included
3. On a scale of 0 to 4, how would you rate the cleanliness of the canteen in the last month?	Included	Not Included
4. In the last month, have you ever worked more than 10 hours in a day?	Included	Not Included
5. Are the fire exits in your factory kept open at all times?	Included	Included
6. In the last month, have you experienced abuse from a manager, such as swearing, physical abuse, or sexual harassment? a. If yes, press 1, if no, press 2. Supervisor_Abuse.wav b. If yes, what type of abuse did you experience: press 1 for swearing, press 2 for physical abuse, press 3 for sexual harassment? Type_Of_Abuse.wav	Included	Included
7. In the last month, have you seen anyone under age 15 working at your factory?	Included	Included
8. Will you recommend this factory to a friend or family member?	Included	Not Included

Table H.1: Questions from Versions 1, and 2 (Continued)		
Questions	**Version 1**	**Version 2**
9. If you have any other feedback on your factory, press “1” or else press “2”.	Included	Included
10. Do you have access to clean drinking water at your factory floor?	Not Included	Included
11. Are you forced to work overtime in your factory to avoid non-payment and getting fired?	Not Included	Included
12. Are you free to join or form trade unions in your factory?	Not Included	Included

Appendix I

Complete stepwise logistic regression and exact logistic regression analysis

Table I.1: Complete stepwise logistic regression and exact logistic regression analysis

Stepwise logistic regression

Mod121

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	11.4276	1	0.0007
Score	9.6613	1	0.0019
Wald	7.5312	1	0.0061

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Sanitation of toilet		1	1	9.6613		0.0019	Sanitation of toilet

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-11.8332	4.1252	8.2282	0.0041
Sanitation of toilet	1	3.8925	1.4184	7.5312	0.0061

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	80.1	Somers' D	0.612
Percent Discordant	18.9	Gamma	0.618
Percent Tied	0.9	Tau-a	0.272
Pairs	544	c	0.806

Mod122

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	8.8601	1	0.0029
Score	8.0106	1	0.0047
Wald	6.5836	1	0.0103

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Sanitation of toilet		1	1	8.0106		0.0047	Sanitation of toilet

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-8.5231	3.1048	7.5357	0.0060
Sanitation of toilet	1	2.7425	1.0688	6.5836	0.0103

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	74.8	Somers' D	0.496
Percent Discordant	25.2	Gamma	0.496
Percent Tied	0.0	Tau-a	0.220
Pairs	544	c	0.748

Mod123

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	8.8754	1	0.0029
Score	7.8853	1	0.0050
Wald	6.5360	1	0.0106

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Sanitation of toilet		1	1	7.8853		0.0050	Sanitation of toilet

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-9.0824	3.3310	7.4344	0.0064
Sanitation of	1	2.9301	1.1461	6.5360	0.0106

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
toilet					

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	77.8	Somers' D	0.564
Percent Discordant	21.3	Gamma	0.570
Percent Tied	0.9	Tau-a	0.251
Pairs	544	c	0.782

Mod124

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.5879	1	0.0181
Score	5.3490	1	0.0207
Wald	4.8399	1	0.0278

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Sanitation of toilet		1	1	5.3490		0.0207	Sanitation of toilet

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-6.0416	2.4613	6.0252	0.0141
Sanitation of toilet	1	1.8581	0.8446	4.8399	0.0278

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	74.1	Somers' D	0.491
Percent Discordant	25.0	Gamma	0.495
Percent Tied	0.9	Tau-a	0.218
Pairs	544	c	0.745

Mod125

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7538	0.3032	6.1817	0.0129

Mod12

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	6.4245	1	0.0113
Score	6.3108	1	0.0120
Wald	5.9671	1	0.0146

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Child_Labor		1	1	6.5506		0.0105	Child Labor

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
2	Sanitation of toilet		1	2	7.0963		0.0077	Sanitation of toilet
3		Child Labor	1	1		3.7969	0.0513	Child Labor
4	Child Labor		1	2	7.7780		0.0053	Child Labor
5		Child Labor	1	1		3.7969	0.0513	Child Labor

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-7.2901	2.1058	11.9852	0.0005
Sanitation of toilet	1	1.7216	0.7048	5.9671	0.0146

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	71.4	Somers' D	0.436
Percent Discordant	27.8	Gamma	0.439
Percent Tied	0.7	Tau-a	0.069
Pairs	2720	c	0.718

Dataset2

Mod12lg1

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Sanitation of canteen		1	1	4.3622		0.0367	Sanitation of canteen
2		Sanitation of canteen	1	0		3.6012	0.0577	Sanitation of canteen

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.6931	0.3693	3.5233	0.0605

Mod12lg2

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	6.7077	1	0.0096
Score	5.5884	1	0.0181
Wald	4.5625	1	0.0327

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.7706	0.7128	1.1688	0.2796
Worker Recommendation	1	-4.5038	2.1085	4.5625	0.0327

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	76.0	Somers' D	0.525
Percent Discordant	23.6	Gamma	0.527
Percent Tied	0.4	Tau-a	0.241
Pairs	242	C	0.762

Mod12lg3

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.0945	1	0.0240
Score	4.7279	1	0.0297
Wald	4.2425	1	0.0394

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.4642	0.6390	0.5277	0.4676
Worker Recommendation	1	-3.5943	1.7450	4.2425	0.0394

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	71.1	Somers' D	0.434
Percent Discordant	27.7	Gamma	0.439
Percent Tied	1.2	Tau-a	0.199
Pairs	242	c	0.717

Mod12lg4

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	9.7885	1	0.0018
Score	7.9496	1	0.0048
Wald	6.3106	1	0.0120

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	1.4814	0.8845	2.8051	0.0940
Worker Recommendation	1	-6.4907	2.5838	6.3106	0.0120

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	81.0	Somers' D	0.628
Percent Discordant	18.2	Gamma	0.633
Percent Tied	0.8	Tau-a	0.288
Pairs	242	C	0.814

Mod12lg5

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.6466	0.3722	3.0184	0.0823

Mod12lg

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7.3998	1	0.0065

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Score	6.3561	1	0.0117
Wald	5.7120	1	0.0168

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Worker Recommendation		1	1	6.3561		0.0117	Worker Recommendation

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.0082	0.5235	3.7094	0.0541
Worker Recommendation	1	-4.0848	1.7091	5.7120	0.0168

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	73.3	Somers' D	0.471
Percent Discordant	26.2	Gamma	0.474
Percent Tied	0.5	Tau-a	0.079
Pairs	1199	C	0.736

Dataset 3

V31

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7.1190	1	0.0076
Score	5.4299	1	0.0198
Wald	4.1004	1	0.0429

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Forced Overtime		1	1	5.4299		0.0198	Forced Overtime
2	Clean Water		1	2	5.0334		0.0249	Clean Water
3		Clean Water	1	1		2.6444	0.1039	Clean Water

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.6105	0.5785	7.7501	0.0054
Forced Overtime	1	4.6730	2.3077	4.1004	0.0429

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	73.8	Somers' D	0.483
Percent Discordant	25.5	Gamma	0.486

Association of Predicted Probabilities and Observed Responses			
Percent Tied	0.6	Tau-a	0.223
Pairs	325	C	0.742

V32

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.6539	0.3419	3.6573	0.0558

V33

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.6539	0.3419	3.6573	0.0558

V34

Note: No (additional) effects met the 0.05 significance level for entry into the model.

V35

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.6931	0.3397	4.1639	0.0413

V3

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	4.8331	1	0.0279
Score	6.8727	1	0.0088
Wald	5.1465	1	0.0233

Summary of Stepwise Selection							
Step	Effect	DF				Pr > ChiSq	

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq

	Entered	Removed		Number In	Score Chi-Square	Wald Chi-Square		Variable Label
1	Forced Overtime		1	1	6.8727		0.0088	Forced Overtime

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.7308	0.3849	50.3471	<.0001
Forced Overtime	1	1.6988	0.7488	5.1465	0.0233

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	71.5	Somers' D	0.435
Percent Discordant	28.0	Gamma	0.437
Percent Tied	0.5	Tau-a	0.074

Association of Predicted Probabilities and Observed Responses			
Pairs	1651	c	0.717

Dataset 4

Mod121

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7538	0.3032	6.1817	0.0129

Mod122

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Cooperative Inspection		1	1	9.2391		0.0024	Cooperative Inspection

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
2		Cooperative Inspection	1	0		0.0027	0.9585	Cooperative Inspection

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7538	0.3032	6.1817	0.0129

Mod123

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7538	0.3032	6.1817	0.0129

Mod124

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7538	0.3032	6.1817	0.0129

Mod125

Note: No (additional) effects met the 0.05 significance level for entry into the model.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7538	0.3032	6.1817	0.0129

Mod12

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	3.5550	1	0.0594
Score	4.7021	1	0.0301

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Wald	4.1876	1	0.0407

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	Cooperative Inspection		1	1	4.7021		0.0301	Cooperative Inspection

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.0594	1.1728	0.0026	0.9596
Cooperative Inspection	1	-1.3122	0.6412	4.1876	0.0407

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	22.9	Somers' D	0.168

Association of Predicted Probabilities and Observed Responses			
Percent Discordant	6.2	Gamma	0.576
Percent Tied	70.9	Tau-a	0.027
Pairs	2720	C	0.584

Exact logistic regression analysis

Mod121-125, 12

```
WARNING: There is not enough memory available for exact computations.

ERROR: The SAS System stopped processing this step because of insufficient memory.
```

Mod12lg1

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.0297	1	0.0249
Score	4.3622	1	0.0367
Wald	3.6012	1	0.0577

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Sanitation_canteen	Score	4.2302	0.0375	0.0375
	Probability	5.167E-9	0.9993	0.9993

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Sanitation canteen	2.4402	1.3037	0.1657	5.3528	0.0331

Mod12lg2

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	6.7077	1	0.0096
Score	5.5884	1	0.0181
Wald	4.5625	1	0.0327

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Recommendation	Score	5.4191	0.0173	0.0173
	Probability	1.033E-8	0.7389	0.7389

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Recommendation	-4.3603	2.0662	-8.9041	-0.7598	0.0134

Mod12lg3

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.0945	1	0.0240
Score	4.7279	1	0.0297
Wald	4.2425	1	0.0394

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Recommendation	Score	4.5846	0.0305	0.0305
	Probability	2.067E-8	0.6766	0.6766

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Recommendation	-3.4768	1.7112	-7.1087	-0.3232	0.0292

Mod12lg4

Not sufficient memory

Mod12lg5

No variable selection

Mod12lg

Recommendation

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	4.8736	1	0.0273
Score	4.3518	1	0.0370

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Wald	3.8586	1	0.0495

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.5906	0.7038	0.7043	0.4013
Recommendation	1	-4.2613	2.1693	3.8586	0.0495

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Recommendation	Score	4.2199	0.0380	0.0380
	Probability	5.167E-9	0.9982	0.9982

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Recommendation	-4.1271	2.1293	-8.7034	-0.2759	0.0340

Exact Odds Ratios				
Parameter	Estimate	95% Confidence Limits		Two-sided p-Value
Recommendation	0.016	<0.001	0.759	0.0340

V31

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7.1190	1	0.0076
Score	5.4299	1	0.0198
Wald	4.1004	1	0.0429

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Forced_Labor	Score	5.2870	0.0056	0.0056
	Probability	1.477E-9	0.3786	0.3786

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Forced_Labor	4.5301	2.2663	0.7132	9.3889	0.0111

V32

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	11.7711	2	0.0028
Score	7.0492	2	0.0295
Wald	4.5430	2	0.1032

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Forced_Labor	Score	2.2223	0.0286	0.0214
	Probability	0.0143	0.4286	0.4214
Clean_Water	Score	4.2308	0.0769	0.0577
	Probability	0.0385	0.6538	0.6346

Note: # indicates that the conditional distribution is degenerate.

Exact Parameter Estimates						
Parameter	Estimate		Standard Error	95% Confidence Limits		Two-sided p-Value
Forced_Labor	15.4397	*	.	1.3871	Infinity	0.0286
Clean_Water	-3.3937	*	.	-Infinity	-0.1958	0.0769

Note: # indicates that the conditional distribution is degenerate.

* indicates a median unbiased estimate.

V33

Not sufficient memory

V34

No Variable Selection

V35

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	3.6924	1	0.0547
Score	3.7042	1	0.0543
Wald	2.5967	1	0.1071

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Forced_Labor	Score	3.6092	0.0408	0.0408
	Probability	1.834E-8	0.1486	0.1486

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Forced_Labor	1.8655	1.1727	-0.1460	4.5224	0.0731

Exact Odds Ratios				
Parameter	Estimate	95% Confidence Limits		p-Value
Forced_Labor	6.459	0.864	92.054	0.0731

V3

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7.1190	1	0.0076
Score	5.4299	1	0.0198

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Wald	4.1004	1	0.0429

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.6105	0.5785	7.7501	0.0054
Forced_Labor	1	4.6730	2.3077	4.1004	0.0429

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Forced_Labor	Score	5.2870	0.0056	0.0056
	Probability	1.477E-9	0.3786	0.3786

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		Two-sided p-Value
Forced_Labor	4.5301	2.2663	0.7132	9.3889	0.0111

Exact Odds Ratios				
Parameter	Estimate	95% Confidence Limits		Two-sided p-Value
Forced_Labor	92.772	2.040	>999.999	0.0111

Mod121

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7.7320	2	0.0209
Score	6.9664	2	0.0307
Wald	4.6657	2	0.0970

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Certified	Score	3.2436	0.1076	0.0747
	Probability	0.0658	0.1076	0.0747
Cooperative_Approach	Score	5.1939	0.0394	0.0212
	Probability	0.0364	0.0394	0.0212

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		p-Value
Certified	-1.9860	1.1899	-6.0894	0.4003	0.1432
Cooperative_Approach	-2.2195	1.1445	-6.1718	0.1840	0.0789

Mod122

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	14.5435	2	0.0007
Score	13.2353	2	0.0013
Wald	3.9002	2	0.1423

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Buyer_supplier_Relat	Score	5.3178	0.0489	0.0260
	Probability	0.0458	0.0489	0.0260
Cooperative_Approach	Score	8.0000	0.0124	0.0062
	Probability	0.0124	0.0124	0.0062

Exact Parameter Estimates						
Parameter	Estimate		Standard Error	95% Confidence Limits		p-Value
Buyer_supplier_Relat	-2.3302		1.1969	-6.3873	0.3163	0.0977
Cooperative_Approach	-2.5489	*	.	-Infinity	-0.6457	0.0124

Note: * indicates a median unbiased estimate and a one-sided p-value.

Mod123

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	6.4611	2	0.0395
Score	6.0611	2	0.0483
Wald	4.2446	2	0.1198

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Certified	Score	2.2945	0.1923	0.1296
	Probability	0.1254	0.1923	0.1296

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Cooperative_Approach	Score	5.1322	0.0406	0.0219
	Probability	0.0374	0.0406	0.0219

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		p-Value
Certified	-1.7775	1.2362	-5.9865	0.7563	0.2755
Cooperative_Approach	-2.1955	1.1416	-6.1440	0.1943	0.0811

Mod124

No Variable Selection

Mod125

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.0056	2	0.0819
Score	4.6672	2	0.0969
Wald	3.8513	2	0.1458

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Certified	Score	2.2442	0.2169	0.1585
	Probability	0.1168	0.2169	0.1585
Buyer_supplier_Relat	Score	3.1537	0.1650	0.1253
	Probability	0.0794	0.1650	0.1253

Exact Parameter Estimates					
Parameter	Estimate	Standard Error	95% Confidence Limits		p-Value
Certified	-1.6037	1.1441	-5.5848	0.6882	0.2681
Buyer_supplier_Relat	-1.4986	0.9041	-3.9837	0.5491	0.1876

Mod12

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	6.0563	2	0.0484
Score	6.6838	2	0.0354
Wald	5.8534	2	0.0536

Exact Conditional Tests				
Effect	Test	Statistic	p-Value	
			Exact	Mid
Certified	Score	1.9606	0.2006	0.1439
	Probability	0.1135	0.3121	0.2553
Cooperative_Approach	Score	4.9990	0.0480	0.0285
	Probability	0.0389	0.0480	0.0285

Exact Parameter Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		p-Value	Odds Ratio
Certified	-1.3748	1.0537	-5.1581	0.5794	0.2786	
Cooperative_Approach	-1.3559	0.6456	-2.7509	0.2306	0.0959	1.149