**ABSTRACT**

SOUNDARARAJAN, BALAJI. Identification of Auditor Bias by Examining Common Method Variance in Supplier Compliance Audits. (Under the direction of Dr. Robert Handfield and Dr. Marguerite Moore).

Many companies increasingly rely on Supplier Compliance Audits (SCAs) to ensure compliance to a code of conduct. Recently SCAs have become more prominent within the textile & apparel industry due to major industrial accidents and ongoing public scrutiny about factory conditions. Despite their prominence, multiple authors have questioned the utility of a SCA as their outcomes can be susceptible to the influence of many factors, including bias. In this dissertation, a unique dataset of consisting of thousands of audits conducted by many auditors over a period of time of a large apparel corporation was examined for the effects of auditor bias. Using the lens of common method bias, a standard definition of auditor bias was developed and SCA categories were examined using structural equation modeling. Additionally, differences in auditor bias between China and the U.S. was examined. The results this study provide direction for identifying and measuring auditor bias. Practitioners can apply the study's insights when assessing auditing protocols.

# Identification of Auditor Bias by Examining Common Method Variance in Supplier Compliance Audits

by
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# DEDICATION

Dedicated to my family, teachers, and the Lord almighty

## BIOGRAPHY

Balaji Soundararajan (Bala) was born and raised in Madurai, Tamil Nadu India and had his schooling from TVS Lakshmi Matriculation Higher Secondary School. He obtained his undergraduate degree in Bachelors of Electronics Engineering (B.E) from National Engineering College, Kovilpatti affiliated with Anna University in May 2005, graduating among the top of his class. After graduation, Balaji worked in various roles at Covansys Corporation & Tata Consultancy Services, performing duties related to development of open-source database MUMPS and was part of the team that engineered *Faster Payments*, a payment system used in the UK and *HMRC Credit Reporting Systems*. Balaji moved to the US in 2010 and obtained his Master's in Business Administration (MBA) from North Carolina State University in 2012. Since then, he has worked in various leadership roles at Xerium Technologies (Now Andritz Pulp & Paper), Apptio & Mu Sigma. In these roles, his work focused on developing complex analytical models related to supply chain security, costs, and demand. Bala was awarded the *IMPACT Award for Excellence* in 2016 for his work on optimizing emergency inventory for a large retailer. Since 2016, he has been a co-author of the *Supply Chain Data Governance & Quality Study*, which is an annual publication of the Supply Chain Resource Cooperative at North Carolina State University. Bala has also spoken at various conferences on topics related to risk management, supply chain security & data quality. He is currently appointed as Teaching Assistant for *Entrepreneurship*, and *Six Sigma* courses at the Wilson College of Textiles. He enrolled for his PhD degree in Textile Technology Management, with a minor in Operations Research in 2018.

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# Introduction

## 1. 1 Problem Introduction

The discussion of transparency in modern supply chains can be traced back to G. W. Dickson's 1966 paper titled "An analysis of vendor selection systems and decisions". Dickson proposed inclusion of compliance procedures, reputation and position in industry to be among 22 attributes organizations must consider while selecting a supplier. In 1995, Nike and Levis Strauss surprised the business community by publishing their supplier lists (Doorey, 2011). Since 2012, The California Transparency in Supply Chains Act and more recently the German Supply Chain Act of 2021 impose significant obligations on companies that source products and services from emerging economies to comply with human rights, labor and environmental standards as outlined by applicable law. In addition, Environmental & Social Governance (ESG) is also used by investors as an indicator to drive investments in companies. According to Morningstar, the total value of assets classified as ESG funds reached USD 3.9 Trillion in September 2021.

Consistent with the emerging corporate emphasis on transparency, Multinational Corporations (MNCs), Multi-Stakeholder Initiatives (MSIs), Non-Governmental Organizations (NGOs), Certification & Regulatory bodies and additional organizations use Supplier Compliance Audits (SCAs) to monitor, enforce and measure compliance among their suppliers. The social auditing process is commonly guided by an organization's specific code of conduct designed to reflect their commitment to social, ethical, and environmental supply chain practices. According to Bartley (2005) Implementation of auditing procedures to monitor or verify opaque supply chain operations has been steadily increasing since the early 21st century. The impact of

widely publicized industrial accidents, such as the Rana Plaza building collapse in 2014 incentivized western brands to engage in social auditing practices to mitigate reputational risk.

Despite increasing rates of adoption, the effectiveness of SCAs continues to be debated among various stakeholder groups in global supply chains (Locke, 2007; Short et al, 2016). Researchers suggest several reasons for SCA ineffectiveness including lack of continuity (i.e., provide a discrete rather than ongoing observation) (Locke et al, 2007; Chen & Lee, 2017) and collusion between suppliers and auditors (Chen at al, 2020). Further, Khalid (2020) suggests that the likely impacts of audit fatigue which occurs from excessive, repetitive auditing activities imposed on factories, impedes SCA effectiveness.

A few studies that consider the potential impacts of auditor bias offer potential directions for improving the SCA process specifically within the apparel industry. Short, Toffel & Hugill (2016) find that audits conducted by teams with higher levels of training, typically yielded more violations compared to those conducted by teams with less training. More recently, Kraft, Liu, Soundararajan, and Handfield (2021) demonstrate the presence of leniency bias among supplier compliance auditors in the apparel industry. Specifically, leniency bias refers to an auditor's tendency to inflate or deflate a factory's social audit performance. Beyond these two empirical examples, insight into the presence and impact of bias among SCA measurement remains underexplored in the academic literature.

Bettinghaus (2014) underscores the inherent subjectivity associated with auditing in general by pointing out that even well-intentioned auditors who are committed to objectivity can unintentionally allow bias to distort their decisions. Given the subjective nature of the SCA process, there is an increased likelihood that auditor bias exists and potentially impacts the outcomes and effectiveness of this effort.

According to Podsakoff, Mackenzie & Lee (2003), the measurement methods used in measuring cognitive/behavioral processes can have underlying biases. In their study they refer to this bias as Common Method Bias (CMB) or Common Method Variance (CMV). Further, they define CMV as the "variance that is attributable to the measurement method rather than to the constructs the measures are assumed to represent." A further clarifying definition for CMV is provided by Richardson, Simmering & Sturman (2009) as "systematic error variance shared among variables measured with and introduced as a function of the same method and/or source". Halo effects, social desirability, acquiescence, leniency & mood are some of the postulated sources of CMV (Podsakoff et al, 2003; Gorrell et al, 2011).

The detection of bias can facilitate mitigation efforts that are capable of ultimately improving the validity and effectiveness of SCAs which require considerable resources for factories as well as additional stakeholders. This research proposes an approach to detect and quantify CMV in SCAs in an effort to improve the overall effectiveness of these activities in global apparel supply chains. Given the increasing complexity of these supply chains, improvements in SCA implementation can provide an effective means for increasing transparency.

To do so, we use data from Supplier Compliance Audits, spread over several years, conducted by a large apparel corporation. Then, we measure this bias in various areas of Supplier Compliance Audits. Finally, we provide an understanding of how bias is affected over the course of an auditor's professional experience.

## 1. 2 Research Purpose and Objectives

The overall purpose of this research is to examine the potential presence and impact(s) of auditor bias on SCA outcomes in the global apparel supply chain. To address this purpose the following objectives are stated:

**RO1:** Is auditor bias present in Supplier Compliance Audits?

**RO2:** Does the occurrence of auditor bias differ among various SCA categories? (Labor, Legal & Environmental, Health & Safety)

**RO3:** Does auditor bias vary between countries?

In answering the first objective, we define auditor bias as the systematic error variance shared among variables measured using the same audit protocol by different auditors i.e., the common method variance arising from auditors using the same instrument.

In the second research question, we examine the data to further understand the differences in levels of bias among various categories of issues audited in Supplier compliance context. Supplier Compliance Audits typically have multiple areas of focus. Within the same auditing protocol, they are typically in the form of questions that address an individual area. In our research, we aggregate the questions in an audit and categorize them into three areas of focus listed below. We then examine which part of Supplier Compliance Audits are more susceptible to auditor bias.

1) Labor Issues
2) Legal & Environment
3) Health & Safety

In many parts of the world, social auditing is a professional undertaking. supplier compliance auditors travel to various factories to perform the auditing function physically. The audits can be conducted as individual audits or by teams of auditors. In the third research question, we analyze the differences in auditors' reporting of factories in different countries.

## 1. 3 Research Scope

The data we use for this research was provided by one large apparel corporation. Hence, it can be stated that this research focuses on analyzing auditing behavior of a large global apparel corporation. The corporation owns a portfolio of brands that overlap apparel, footwear, and accessories. The motivation of the research was to understand audit outcomes at organizational level and design cross-training programs for auditors across geographies. The research was performed retroactively on data collected in the past. The analysis was performed in a general social auditing context and no controls were adopted on how the audits were conducted. All audits conducted by the corporation are tied to a code of conduct, which did not change during the duration of analysis. The auditing function is entirely owned by the corporation, though the company may utilize third-party auditors for additional auditing capacity. The reader can find a detailed description of the data in Chapter 3

In general, audits are defined as "independent examination of financial information of any entity, whether profit oriented or not, irrespective of its size or legal form when such an examination is conducted with a view to express an opinion thereon" (Wikipedia, 2021). Supplier Compliance Audits can be considered as a subset of audits focusing on social performance of a firm or factory. They typically focus on examining a factory's compliance to standards in various categories. In examining the code of conduct of our corporation, we broadly

categorized their Supplier Compliance Audits to focus on Labor Issues, Legal & Environmental performance, Health & Safety and Others. Not all Supplier Compliance Audits may cover all issues related to the categories mentioned above.

There exist multiple standards that govern a Supplier Compliance Audit such as Social and Labor Convergence (SLCP), Worldwide Responsible Accredited Production (WRAP), UN Global Compact etc. However, many large corporations and brands create their own standards for Supplier Compliance Audits or may choose to accept one or many of the standards available in the market. The corporation in our study uses their own code of conduct as the standard for conducting Supplier Compliance Audits. Within this research, the term "audits" and "assessments" are used interchangeably. A detailed description of the auditing protocol used in this research is provided in Chapter 3.

## 1. 4 Research Benefits

The social impact of an apparel company's supply chain is subject to increasing scrutiny today (Egels-Zanden et al, 2016, 2017; Yu, 2019; Hasan et al; 2019; Liu et al, 2019). Corporations recognize the need for socially responsible behavior of their suppliers, such as avoiding child labor, ensuring safe working conditions, decent pay among others and seek to exemplify these virtues in the codes of conduct. Apparel Brands and Corporations audit their suppliers for compliance with these codes as view non-compliance as a risk to their reputation (Short et al, 2016). In a global supply chain, SCAs are hence regarded as necessary to reduce the reputational risk to a corporation.

The outcomes of this research can inform the design of auditing procedures including instrument design, auditor training and administrative protocol for stakeholder organizations

with an interest in supplier compliance. The research setting allows for examination of similar effects in other organizations in the textile/apparel industry. In a broader supplier compliance context, we believe some outcomes of this research can also be used to examine other industries e.g., electronics. This research contributes to the supply chain risk management (SCRM) discipline by allowing managers to construct training and processes that can be used to make aware of and decrease bias in their organizations.

## 1. 5 Structure of Dissertation

The Chapter 1 of the dissertation introduces the context and research questions, along with the related background and scope

Chapter 2 provides a review of extant literature related to the context. It identifies potential gaps in literature and the contribution of this study.

In Chapter 3, discusses the data & methodology adopted in this research.

Chapter 4 presents, interprets & discusses the results

Chapter 5 concludes by providing implications and future direction of the study.

The Appendix section contains supplementary materials required to interpret this study.

The References section contains references to tables and other sources used to perform this research.

# CHAPTER 2

# Literature Review

## 2. 1 Auditing Suppliers

The social auditing process is commonly guided by an organization's specific code of conduct designed to reflect their commitment to social, ethical, and environmental supply chain practices. The overall application of auditing procedures tied to a code of conduct to monitor or verify opaque supply chain operations has been steadily increasing since the early 21st century (Bartley, 2005). Within the apparel industry the propensity of social auditing practices has accelerated by the 2014 Rana Plaza building collapse in which 1000 Bangladeshi factory workers died. Despite increasing adoption of Supplier Compliance Audits (SCAs) their effectiveness is commonly debated among various stakeholder groups (Locke, 2007; Short et al, 2016). Researchers suggest several reasons for SCA ineffectiveness such as: lack of continuity (i.e., discrete rather than ongoing) (Locke et al, 2007; Chen & Lee, 2017) and collusion between suppliers and auditors (Chen at al, 2020). Additionally, as SCAs continue to proliferate in the apparel industry, factories are starting to complain of audit fatigue arising from frequency and complexity of audit related activities and their impact on factory productivity. (Kraft et al, 2021; Khalid et al, 2020).

Aside from recent efforts by Kraft et al. (2021), Ibanez & Toffel (2020) and Short, Toffel & Hugill (2016) who focus on the presence of bias in auditing within their respective studies, little consideration of SCA effectiveness is evident in the academic literature. As mentioned in the Introduction, Kraft et al (2021) report the presence of leniency bias among SCAs generated in the apparel industry. Among other effects, they report that auditor leniency is often

accompanied by a greater reduction in risk in subsequent audits. Similarly, Ibanez & Toffel, when examining food safety inspections, note the presence of negativity bias among auditors, causing factories which had prior violations to report more violations. One particularly interesting observation noted in the same study was how inspectors cited fewer violations towards the end of the day, than during the beginning of the day, indicating time of audit could affect outcomes. Earlier, Short, Toffel & Hugill in 2016 reported that auditors with higher levels of training tend to identify a greater number of violations, though the focus of the study was not auditor bias. Besides, the quality of noncompliance findings reported by auditors in a professional setting remains studied to an even lesser extent. No study we reviewed studied the differences in levels of bias within categories or settings typically handled in a Supplier Compliance Audit or examine period effects on auditor bias.

As such, individual biases of auditors could affect the overall supplier compliance program of a corporation or any other auditing body. Such an effect could affect the overall quality of SCAs performed by that organization and by extension the supplier compliance program itself. While the effect of some biases on audit quality may be apparent, it may be impossible to identify all types of biases affecting an auditing organization. This is because biases can originate from various sources and from a variety of reasons. Already, the causes of some biases in auditors have been attributed to anchoring, cultural effects, overconfidence, and groupthink, among others (Bettinghaus, 2014). Additionally, organizational culture could also have some influence on the origins of auditor bias, since it is among the systematic contributors to other known bias originators such as groupthink & overconfidence (Shore, 2008). It can hence be argued that auditors of the same organization, who are used to performing audits using similar

methods developed as a result of organizational culture, potentially have similar but varying levels of biases.

## 2. 2 SCAs in the Apparel Industry

To develop further understanding of auditor bias specific to this study, we studied the background of SCAs in the apparel industry. Initial efforts for supplier compliance by corporations focused on compliance with respective national regulations & laws in general (Jenkins, 2001). In response to several major scandals in the 1980s such as Nestle's marketing of breast milk substitutes in Latin America, and The Bhopal Gas Tragedy, corporations started to adopt codes of conduct (COC) as a way to codify good business practices. In this early wave, the COCs were focused mainly on matters related to conflicts of interest, bribery, and sexual harassment (Bartley, 2005). The apparel and footwear industry's foray into supplier compliance began in the 1990s with the creation of voluntary codes of conduct by corporations like Nike and Levis. The adoption of these codes was seen as a defensive mechanism in response to criticism from NGOs and governments (Doorey, 2011). Compliance audits were then instituted as tools to verify performance against these codes of conduct. These audits are referred to by various names, among which the term "Social Compliance Audit" was popularized by the ``Economic Review" magazine, published out of Karachi, Pakistan (Ebrahim, 2003).

The Rana Plaza incident in 2014, brought renewed scrutiny to the effectiveness of social auditing activities. Egels - Zanden et al (2013, 2014) while examining the effects of code of conduct in the toy industry argue that audits only have served to promote the interests of brands and have not resulted in improvements on the ground, thereby not improving any underlying risk. Their study focuses on the empirical effects of whether or not private regulation and codes of conduct improve workers' rights on the factory floor using the SCAs conducted by the

International Council of Toy Industries (ICTI). However, within the apparel industry, an argument has been made that, factories subjected to auditing of working conditions would improve over time and that the cooperation by suppliers to being audited is an indicator of the risk associated with working conditions, with less cooperation indicating higher risk (Lindholm et al, 2016; Liu et al, 2019). Many authors though emphasize the need for other complementary mechanisms such as effective government regulation (Yu, 2007, 2008), equitable standards (Lindholm, 2016) and integrated management processes (Locke et al, 2007; Distelhorst et al, 2016) to improve the effectiveness of SCAs.

Accordingly, different organizational methods have evolved to carry out SCAs. Some factories perform SCAs as self-assessment which are then subject to verification at a later time. One example of this approach is SLCP Common Assessment Framework. Factories audited through this multi – stakeholder initiative (MSI) initially submit a self-assessment which is then verified by an appointed "verifier." In some other cases, SCAs can be conducted by certification bodies such as Fair Wear Foundation that certify the adherence of a factory to a standard (Lindholm, 2016). Alternatively, SCAs can also be performed by auditors employed directly by the buyers or it can be outsourced to third-party contracted auditors (Short et al, 2016; Liu et al, 2019; Yu, 2009).

### 2. 3 Measuring and Understanding SCA Outcomes

Prior research has taken multiple approaches to examine the effectiveness of audits and audit outcomes in general. One of the first approaches to measure audit outcomes in a supplier compliance context was by Nike using a scoring system referred to as the "M-audit" (Locke et al, 2007). Under the M-audit scoring system, a factory with perfect compliance was rated 100, while a factory with no compliance was rated lower. When this method was examined by Locke,

Qin & Brause in 2007, the average score for all factories then audited by Nike was 65. indicating just about a third of them were compliant. Later, Short, Toffel & Hugill in their 2016 paper, focus their measurement on the number of violations reported in a SCA. In their study, the SCA outcomes are hypothesized to depend on various factors described as 1) previous experience of the auditor at the factory 2) the maximum tenure of the auditor 3) average tenure of the auditing team 4) education levels of the auditor 5) type of training provided to the auditor 6) the gender composition of the auditing team 7) certification & brand related training provided to the team 8) average age 9) type of audit (internal/third-party) 10) scheduled/unscheduled audits 11) payee responsible for the audit 12) number of auditors 13) audit sequence 14) GDP of the country 15) regulatory quality in the country, and 16) press freedom.

We also studied audit outcome measurement outside of SCAs, in contexts of other types of audits. One of these models, especially used by the software industry, is the method of providing a "maturity score" to an organization (Bhattacharya et al, 2013). In this method, an organization that is rated as more mature is audited at a lesser frequency for items different from that of an organization considered to be of lower maturity. In this audit maturity model called CMMI (Capability Maturity Model Integration), an initial maturity score is assigned to an organization and subsequent audits that happen at the organization have questions that increase in complexity. Organizations go through five levels of maturity labeled as "initial," "managed," "compliant," and "mature," before reaching the highest level "optimizing". The "initial" maturity level typically corresponds to organizations that are reactive and chaotic. In the next level "managed," the focus is on process maturity and data quality. By level 3, the organizational and audit focus is on quality of products/services, while shifting to preventive measures by level 4.

At level 5, an organization is considered to overcome systemic problems associated with compliance and the expected focus is on customer relations, transparency etc.

One other approach to measure audit outcomes related to supplier compliance is provided by Distelhorst et al (2016). Their study used a method where the audit outcome measurement combined general compliance metrics with production process maturity. This approach was shown to improve compliance in Labor, and Health, Safety & Environment (HSE) areas of Nike's suppliers. SCAs were conducted in factories where the use of lean manufacturing processes was also noted. It was found that organizations that adopted lean production practices exhibited better labor & HSE compliance. Though, the authors also noted an increased variability of scores associated with these factories. The authors point that such auditing practices could lead to "managed outcomes" potentially because of selection bias, where only a few factories that meet a specific criterion could be chosen to be audited (Distelhorst et al, 2016).

### 2. 4 Theories and Frameworks for improving audit effectiveness

Despite the widespread notion that supplier compliance programs offer only limited improvements (Egels-Zanden, 2007; Locke, 2013; Distelhorst et al, 2016), there are few alternatives offered or explored in the literature (Harrison & Scorse, 2010). Additionally, while industry efforts have focused on reducing the cost of audits, through development of technologies like remote audits (BSI America, 2021); academic efforts focus on exploring ways to better identify and predict audit outcomes (Hugill et al, 2016; Short et al, 2016; Ball et al, 2017).

Perhaps, developing a theoretical framework that analyzes audit outcomes and provides targeted improvements could deliver better outcomes. A theoretical framework to analyze audit outcomes in the form of leniency bias using Item-Response theory has been developed by Kraft

et al (2021). In this study, the theoretical basis is drawn from item-response theory (IRT) which is similar to the techniques employed to analyze standardized tests administered to students. The IRT framework, when employed to analyze possible outcomes of all questions in the audit instrument, provides a probabilistic measure of violation severity.

Among other measurement frameworks used to measure audit outcomes is one that derives its origins from risk management. This approach may be more useful since audits in general are inherently used to measure risk. Other advantages of adopting tenets from risk management is the possibility to analyze risk outcomes even a part of an audit. For example, let us consider subcontracting - which typically is just one part of a SCA. Caro, Lane, and Sáez de Tejada Cuenca (2021) in their paper focusing on unauthorized subcontracting argue that subcontracting of previous orders, lower unit price, and products that are atypical to the supplier increase the likelihood of unauthorized subcontracting, and thereby the risk. Another approach to understanding audit outcomes involved implicit risk measures. In the paper "Improving working conditions in supply chain" by Short et al implicit risk measures such as number of violations are directly used to measure the effects of audits in mitigating reputational risk. The authors state that private governance structures such as codes of conducts, when adopted in response to private political activism, can alter market behavior without the need of a state-based regulatory actor. Their study further provides a five-point framework where suppliers will improve practices:

1) Suppliers will improve their labor practices more when located in institutional environments with civil society monitoring mechanisms.
2) Suppliers will improve their labor practices more when they produce for buyers that have already been publicly exposed for harms to workers in their supply chain.

3) Suppliers will improve their labor practices more following code-of-conduct audits conducted by audit teams that are more highly trained.
4) Suppliers that receive advance notice of code-of-conduct audits will improve their labor practices more than other suppliers.
5) Suppliers audited by highly trained auditors will improve their labor practices more following announced code-of-conduct audits than following unannounced audits.

## 2. 5 Factors that impact audit outcomes

Despite the existence of frameworks to improve audit effectiveness such as audit outcome measures the measure risk, the impact of various factors that affect such outcomes is not clear. In trying to understand these factors, we start with the understanding of individual effects of auditors. In measuring individual impacts on audit outcomes, prior research generally defers to studies about audit quality and audit decision making. Due to the paucity of this information about SCAs, we had to look into studies about audits in general to develop our understanding. We noted considerable variability in the conclusions provided by these studies.

*Auditor Aggressiveness*

Nelson & Tan (2005) state that auditors in general need to perform a variety of tasks to form an overall assurance or attestation opinion. To do so, auditors rely on their personal attributes (e.g., skills, interaction, and personality) which influence the auditing task. On the other hand, auditing outcomes are also constrained by the quality-control mechanisms within the auditing firm (Gul et al, 2013). Within financial audits, such individual effects may be insignificant for one audit. But when the same auditors audit an organization for multiple years and multiple times, the individual effects of an auditor may be significant. One such individual

effect that Gul, Wu & Yang study is auditor aggressiveness. The variation in this trait, which can be explained by auditor demographics, was found to influence auditing outcomes. Other factors which played a role were:  educational background, exposure of the auditor, and size of the organization. For SCAs, the effect of some of these individual characteristics has been explored, while others such as exposure, auditor aggressiveness have not been explored.

*Disparate laws & regulations*

The social auditing profession typically requires auditors to travel to different countries and different regions within the same country. These countries and regions often have varying laws and regulations concerning labor, wages, environment, and other areas. In such scenarios an auditor's role could take the form of an intermediary, separate from rule makers and targets, but an essential part of this ecosystem (Phillip, 2019; Havinga & Verbruggen 2017). Many studies also criticize the analytical choice of separating auditors from rule makers. But Havinga & Verbruggen (2017) also state that due to the inherent complexity in auditing, auditors could also simultaneously function as regulators, intermediaries, or targets. This multi-faceted role of an auditor provides for many avenues that could affect auditing outcomes. For instance, while evaluating labor rights as part of social audits, auditors may lack formal legal expertise or authority specific to the factory being audited. For instance, let us consider the interpretation of Freedom of Association (FoA) SCA category in China & Vietnam by auditors of the Fair Labor Association. According to Phillip, 2019, auditors commonly identified more measures in the recent past, when compared to earlier years given a same legal setting. This observation cannot specify whether it reflects increased elaboration of an otherwise consistent auditing approach or if auditors contributed to the development of new interpretations of FoA. Auditors, who have to

deal with disparate regulatory and legal environments, may have reasons that influence the interpretation of these laws. This affects how audits are associated with diverse cultures and geographies. Cowperthwaite (2010) states that the level of power distance, uncertainty avoidance, and traits of individuals/collectivism determine the cultural perception of audits.

*Technology*

One solution that is being proposed to bring in consistency to audit outcomes is the adoption of technology. But the adoption of technology to aid audit analysis has been slow. Distinct types of audits show various levels of technology adoption when classified based on type of review undertaken in an audit i.e., financial, operational, management & compliance reviews (Ramamoorthi, 2003). Historically, developments in audit technology have been promoted by auditors as technical improvements to the standard of audit work (Power, 2003). Over the past two decades, due to the increasing role of Information Technology, audits have evolved to include electronic work papers and decision aids that employ analytical design approaches. (Janvrin et al, 2008). In 2020, the use of drones and automated counting technology was demonstrated in audits, with purported gains in audit quality and productivity (Christ et al, 2020). The international travel restrictions that were put in place due to the COVID19 pandemic in 2020, has also driven the industry to adopt remote auditing practices (Castka et al, 2021). Further, the introduction of statistical sampling, the audit risk model and business risk auditing approaches are also believed to have increased the scientific nature of audits (Salijeni et al, 2021). However, the increasing adoption of technology has been perceived to reduce independence to auditors and those being audited. (Salijeni et al, 2021). Issues stemming from data quality, multiplicity of standards and costs continue to affect the development and adoption

of technology to aid audit outcomes. (Salijeni et al, 2021; Eulerich et al, 2020; Bakarich & O'Brien, 2021).

*Buyer-Supplier relationships*

The understanding of how buyer-supplier relationships impact audit outcomes begins with the understanding of how buyers perceive auditors and the factories they audit. Liu et al (2019) state that working condition risks in supplier factories are negatively associated with supplier trustworthiness and retailers are more likely to contract with factories that have lower working condition risks, especially in fire safety, building safety & electrical safety. Prior research also indicates that buyers tend to prefer factories which have more resources to address the buyer's concerns on social responsibility, which typically tend to be larger factories (Besiou & Van Wassenhove, 2015; Liu et al, 2019). This is primarily due to the nature of factory safety and production efficiency being of complementary nature to each other (Pagell et al, 2015; Levine & Toffel, 2010).

The behavior of buyers of large firms in developing socially responsible supply chains can be counter-intuitive, due to the complexities and unfamiliarity associated with various stakeholders. This influence of various stakeholders can be addressed in a variety of ways, including the use of auditors, providing more tools to address the power distance between buyers and suppliers. (Darnall et al, 2009; Limajatini et al, 2019). While the attitudes of buyers towards audits have been well understood, there is a general lack of research into supplier attitudes towards auditing (Porteous et al, 2015; Short & Toffel; 2016; Distelhorst et al, 2016). For instance, the coalition of suppliers called Sustainable Textiles for Asian Region (STAR) was recently formed and expanded to include manufacturers of Bangladesh, China, Cambodia,

Pakistan, Myanmar & Turkey, has called for a complete "reset" of buyer-supplier relationship on account of sourcing squeeze by buyers (Jasmin, 2021). While supplier attitudes are generally favorable towards implementation of new technology (such as RFID), their attitude towards new compliance requirements tend to vary (Hingley et al, 2007; Hartford, 1978). Further, studies examining auditor characteristics tend to hold auditors as agents of buyers sometimes or to be in collusion with factories other times (Phillip, 2019; Short et al, 2016; Ball et al, 2018). While auditors may indeed act as regulatory intermediaries, the circumstances shaping their role in favor of the buyer or factories is seldom discussed. No studies we reviewed studied the evolution of the auditor or an auditing organization or the buyer/supplier attitudes towards auditors, which we highlight as a gap in literature.

The primary purpose of corporate-level audit processes continues to be focused on site-level improvement, rather than external accountability (Kemp et al, 2012). The lack of reform in corporate governance to extend stakeholder accountability and facilitate action has reduced the expected improvements possible due to audits (Cooper & Owen, 2007; Kemp et al, 2012, Yu, 2008). Changing industry regulation and increased competition in audits, while having reduced audit fees, has also served to reduce audit quality and reduced cooperation within auditors (Knechel, 2016). The lack of appropriate benchmarks to measure audit quality, has led to proliferation of standards, leading to "audit fatigue" within the factories (Habib, 2011; McKinnon, 2012). All these factors have led to what is called "audit culture," where the proliferation of audits is often not tied to expected outcomes. (Shore & Wright, 2015; Power, 2003).

## 2. 6 Audit Impacts on Business Outcomes

Many large corporations often require their suppliers to "pass" Supplier Compliance Audits in order to be able to accept orders (Nike Code of Conduct; 2020; H&M supplier code of conduct, 2021; VF Corporation code of conduct, 2021). Non-adherence to a code of conduct, can hence constitute a significant business risk for the supplier and a source of reputational risk for the buyer. However, there is a marked disparity on the impact of audits on business decisions. For instance, the Enforcement Guidelines of Adidas Corp (2021) states the employment of prison labor, life-threatening health, safety & environmental conditions, and repetitive & systematic abuse to be of "Zero Tolerance". On the other hand, the compliance handbook of H&M, called the "H&M Way" is more ambiguous on these specific issues. More specifically, H&M's code of ethics for suppliers and business partners list only bribery and corruption as "Zero Tolerance" behavior. Existing literature consequently is limited on establishing causative relationships between SCAs, audit outcomes and business decisions. There is very little evidence that, all things being equal, the MNCs exert much in the way of resources or effort to assess the reliability of these audits. Instead, audits appear to have a symbolic role and allow the MNCs to continue to make claims that appear to play well with western consumers (Islam et al, 2018).

According to Islam et al (2018), the business outcomes attributable to audits are twofold. One being the minimization of risk to the purchasing companies and the other being legitimizing the act of using garment manufacturers in developing nations. In this context, using SCAs to explain the root causes of social non-compliance could increase the value of Supplier Compliance Audits to both manufacturers and buyers. Such an approach of root cause analysis has been applied to financial audits, where examining the insolvency risk has been shown to

provide explanatory power in insolvency situations and firms that are of minimal risk of insolvency tend to have “clean” audit reports (Munoz-Izquierdo et al, 2019).

Another approach to increase the business decision support provided by audits could be the adoption of big data technologies. By identifying the information relevant to auditing processes, big data methods can be used to assess the risk projected by audits (Brown-Liburd et al, 2015). Since MNCs tend to drive their audits, priorities based on external events such as media coverage, the use of automated techniques to analyze audits have the potential to impact audit priorities and outcomes of audit findings (Islam et al, 2018; Brown-Liburd, 2015). The computation of an audit-risk model using the data from audits could potentially address the deficiency in conventional methods of evidence gathering (Salijeni et al, 2019).

## 2. 7 Measuring Bias in SCAs

Prior research suggests that limitations in information gathering, computing abilities and a limited memory do not allow individuals to examine all possible alternatives in a complex decision-making environment, thus forcing the adoption of simpler decision-making strategies such as heuristics, which can expose their decisions to various forms of bias (Carter et al, 2007). Supplier compliance auditing is a sufficiently complex function (Delbufalo, 2018), which often requires hours and sometimes days to cover all areas of the factory and the audit (Egels-Zanden, 2014). Bounded rationality naturally limits the number of issues an auditor can pursue, and bounded awareness causes some individuals to overfocus on some information and fail to use other available information, which may otherwise be easily available (Short & Toffel, 2016). The effect of numerous factors that drive these biases are examined by various authors, with specific focus on prior relationships of an auditor with the supplier, the total number of audits conducted by the auditor over their experience, the level of professional training, gender, and gender

diversity (Short et al; 2016). Other factors that give rise to biased reporting of violations include misaligned incentives for auditors, inadequate training, and suppliers' elaborate efforts at subterfuge (Short et al, 2020). All these factors hence point to bias in SCAs, which in turn affect audit quality.

In trying to examine the elements that drive these biases in greater detail, researchers have discovered many types of biases and their drivers. For instance, Kraft et al (2021) note that bias due to monitor leniency (or leniency bias) is a widespread problem, where an auditor can inflate or deflate the differences in a factory's Corporate Social Responsibility (CSR) ratings. Short & Toffel (2016) also note that leniency can stem from relationships in the auditing firm, factory, and buyer triumvirate. The quasi-judgmental nature of audits, make auditors prone to other types of cognitive biases. Bettinghaus et al (2014) describe eight such biases common in financial audits. They include Rush to Solve, Groupthink, Judgment Triggers, Overconfidence, Anchoring, Availability & Self-Interest. Awareness about bias is often the first step in its mitigation (Bettinghaus, 2014).

Various contributing elements have been studied to understand the effect of bias on audit quality. Gul et al (2013) in studying the effect of individual effects on audit quality, consider auditor aggressiveness to be a key variable of measure. In their study of financial audits, they estimate auditor aggressiveness by identifying the presence of modified audit opinions (MAOs) every year, based on the outcome of the previous year. Similarly, the international work experience of an auditor has also been found to significantly affect the quality of financial audits. Building on the work of Gul et al (2013), Chen et al (2017), consider the international experience of an auditor as the variable of interest. Their study establishes that international work experience improves audit quality.

However, SCAs are often not subject to the same decision standards as financial audits. For instance, the outcome of a financial audit may be expressed in the form of Modified Audit Opinions (MAOs) (Gul et al, 2013; Chen et al, 2017). SCA outcomes on the other hand have different measures. Short et al (2016) use the measure number of violations noted while Kraft et al (2021) focus on severity of violations noted. Dharmasiri et al (2021) in identifying the consequences of ethical audit violations, count both the frequency and severity of violations noted. In the latter case, the presence of dual measures of frequency and severity can be positively associated with auditor integrity and recklessness. It should be noted that Lowrance in 1976, defined risk as a measure of probability and severity of adverse effects.

Many studies support the contention that retailers are sensitive to working condition risks in a supplier factory; that is, an increase in working condition risks in a supplier factory is associated with a corresponding decrease in supplier trustworthiness (Liu et al, 2019). The increased visibility and public disclosure of working condition risks in supplier factories not only reduce heterogeneity in standards across factories but also promote greater awareness of these standards among factories and their stakeholders (Kraft et al, 2018). While few factories conduct regular audits of working conditions and worker safety issues on their own, even fewer are willing to reveal such information for external scrutiny (Short et al, 2015).

# CHAPTER 3

# Methodology

## 3. 1 Methodology Introduction

In this chapter we provide the details into the research design, data, development of measures and concepts, and the statistical tools used to perform the analysis. A description of the proposed steps and process involved in this research is provided in Figure 3.1.

Motivated by the need to understand auditor bias in SCAs, we sought audit data from a large apparel corporation whose name is withheld due to confidentiality. The corporation provided us with data from their SCAs, conducted over a period of 5 years from 2015 to 2019. In addition, information related to organizing, classifying, and analyzing the audit data was obtained from both proprietary and public materials provided by the corporation and through additional conversations with the compliance team and management of the Corporation.

This chapter is organized as follows:

1) Defining auditor bias
2) Data Collection
3) Collection & organization of supplemental information
4) Focal SCA Categories
5) Analytical Model
6) Measures and Datasets
7) Analysis steps & planning

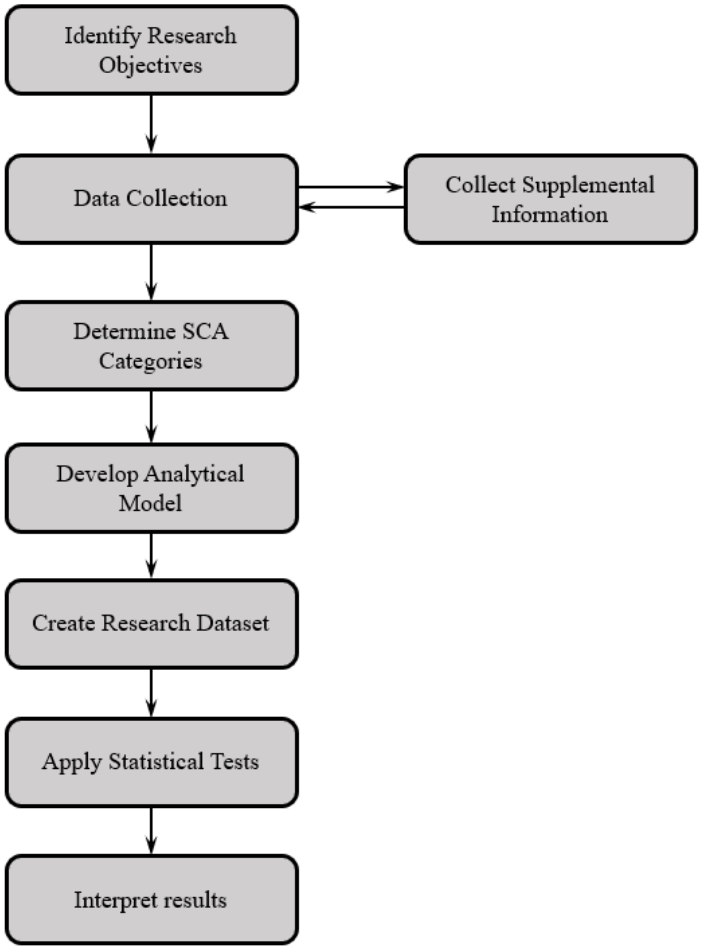



**Figure 3.1: Research Activities**

## 3. 2 Defining auditor bias

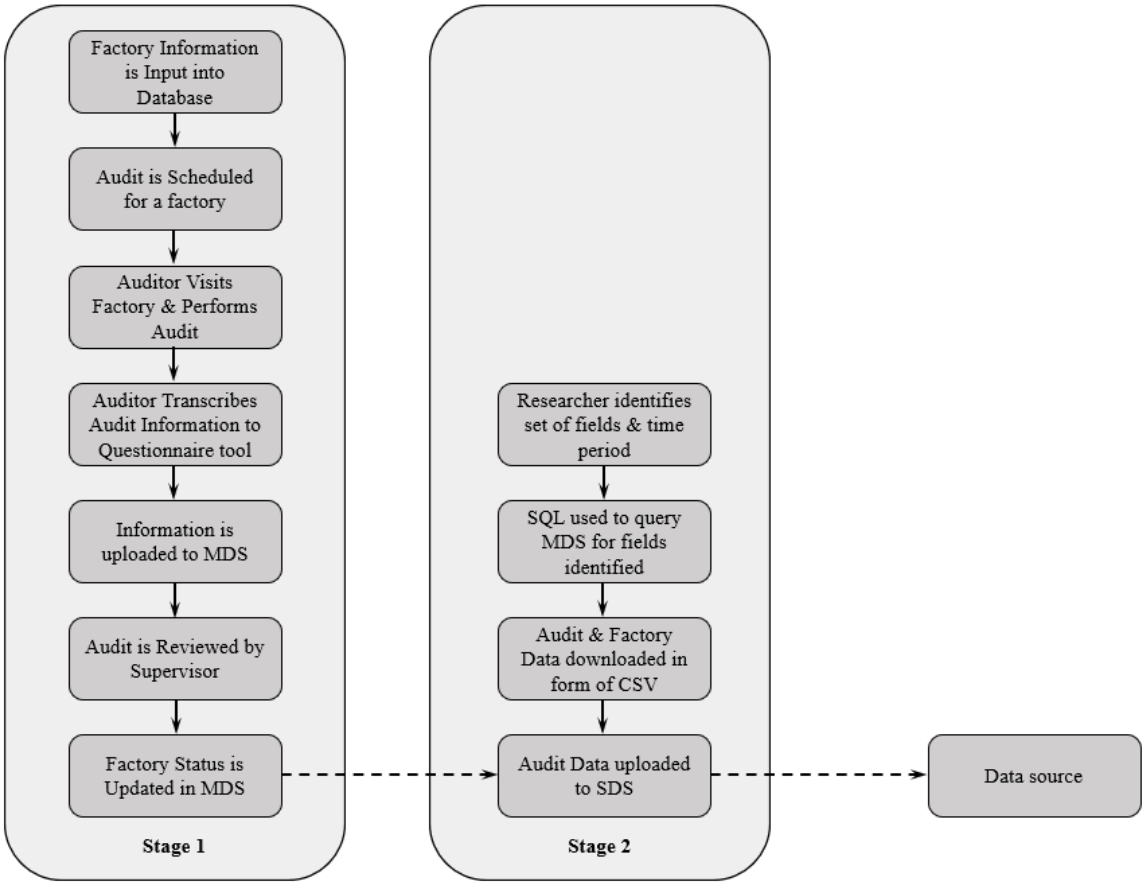
Our definition for auditor bias is framed through the lens of CMB. We define auditor bias as *the systematic error variance shared among audit categories measured using the same audit protocol by different auditors.*

## 3. 3 Data Collection

The data collection process began with studying the code of conduct of the corporation, which was a publicly available document. The researcher then set up meetings with the

corporation's compliance management team to understand the various standards tied to the code of conduct. It was found during the discussion that while the corporation accepted multiple standards for compliance, most of the audits were conducted directly using an internal auditing protocol (or questionnaire). Any audits conducted based on other standards were translated to the internal auditing protocol before input into the database. The corporation maintained a set of guidelines which was used by the auditors to input audits conducted using the internal protocol and other accepted audit standards.

The data collection process for this study was made facilitated by the database used by the corporation to collect and store audit data. The audit data stored in the database was input using a standardized process upon on which all auditors of the organization were trained on. A description of the data entry process is provided in Figure 3.2.




MDS = Master Data Store, SDS = Sample Data Store

**Figure 3.2: Data Collection Process**

The data collection process for this study comprised of two stages. In the first stage, auditors representing the corporation visited individual factories. The visits to a factory were scheduled in advance. During the audit, the auditor would physically visit applicable units in the factory and note their observations in an auditing tool. The auditor would then transcribe the information collected into the standard auditing questionnaire of the corporation. The transcribed audit is then input into the database, where the audit is matched to the factory it was conducted. This database was designated as Master Data Source (MDS).

In the second stage of data collection, the researcher developed a set of Structured Query Language (SQL) programs to obtain specific data related audits and audit history of a factory. The results provided by the SQL queries were then securely downloaded into a CSV (Comma Separated Values) file. Due to the large volume of information obtained in each query, the researcher repeated the process for every month of the study. In all, the process was repeated 60 times, which yielded audit data over a 5-year period (2015 to 2019). Then, the researcher transferred the data from the CSV files to another database where it can be analyzed along with other types of data collected from supplemental materials. This database was designated as the Sample Data Source (SDS). After establishing the SDS, no further data was collected from MDS.

### 3. 4 Supplemental Material Used

In addition to audit data, supplemental information was collected from the Corporation's Code of Conduct (COC), Terms of Engagement (TOE), and Auditor's Manual. The information collected from these materials are detailed in this section.

The corporation's COC identified its primary goals for ethical behavior related to conducting business. The COC encompasses many goals that cover responsibility & integrity, commitment to follow the law, and management practices. In addition to the COC, the corporation specifies 17 compliance principles expected of suppliers referred to as Terms of Engagement (TOE). We use the TOE principles as the basis for distinguishing the focal SCA categories. Among the TOE principles, five principles were not retained for the analysis because they fall outside the conceptual scope (i.e., list them)

After consideration of the COC and TOE, the corporate auditor's manual was reviewed to understand the auditing process in greater detail. This document contained explicit instructions

for the evaluation process including the sequence of steps used to determine non-compliance. The auditor's manual provides 56 questions related to the 17 principles, which form the framework for the company's SCAs. The 12 focal SCA Categories identified for further analysis were grouped into three "Super Categories". The Super Categories were designated as Health & Safety, Labor, and Legal & Environment. Table 3.1 describes the relationship between Super Categories, focal SCA Categories and the number of questions subsumed within these categories.

**Table 3.1: SCA Categories & Number of Questions for Each Category**

| Super Category | Focal SCA Category | Number of Questions |
|---|---|---|
| Health & Safety | Health & Safety | 28 |
| Labor | Child Labor | 2 |
| | Forced Labor | 1 |
| | Freedom of Association & Collective Bargaining | 3 |
| | Harassment or Abuse | 1 |
| | Hours of Work | 2 |
| | Non-Discrimination | 1 |
| | Wages & Benefits | 9 |
| | Women's Rights | 1 |
| Legal & Environmental | Environment | 1 |
| | Informed Workplace | 1 |
| | Legal Compliance | 2 |

The auditors' manual also provides specific criteria for determining audit outcomes (i.e., pass/fail) at the individual question level. Each binary response was required to be accompanied by a three-point ordinal indicator of severity (i.e., high, moderate & low). Further, the manual

also provides country specific exceptions that apply to specific questions. If an auditor assigns a violation to a question, they were required to substantiate this decision with supplemental evidence typically in the form of photographs or narrative explanations.

### 3. 5 Focal SCA Categories

In total 52 of 56 original audit questions were grouped into 12 Categories called Focal SCA categories. These SCA Categories were then further aggregated into three Super Categories: Health & Safety, Labor, and Legal & Environment based on audit scope. The Health & Safety Super Category comprised of a single SCA category and 28 unique questions, while the Labor Super Category comprised eight SCA Categories and 21 unique questions. Finally, the Legal & Environmental Super Category included three SCA Categories and four unique questions. In the following sections, we describe each SCA Category and their questions in detail, followed by an explanation of the rationale for further aggregating the SCAs into Super Categories.

#### 3. 4. 1 Health & Safety Super Category

The Health & Safety Super Category included the largest number of questions mapped to a single SCA category. This Super Category covers the factory work environment with regard to cleanliness, safety and health and is intended to prevent factory accidents. The 28 questions in this category cover the following areas:

1. Existence of an effective health & safety program, including local codes as applicable.
2. Determine if the facility has personnel who are trained on all health & safety procedures as applicable.
3. Determine if the facility has first aid supplies that are accessible and in working order.
4. Determine plans, policies & procedures for serious injuries.
5. Review lock-out procedures.

6. Determine practices and training related to handling hazardous materials and chemical safety.
7. Availability of emergency evacuation diagrams (incl local languages).
8. Determine if emergency alarm is installed, in working condition and can be heard in all areas of the factory.
9. Determine if emergency evacuation drills are conducted periodically.
10. Determine if adequate, accessible, operable, unblocked & working emergency exits are available.
11. Determine if aisles on the factory floor are clear of obstructions.
12. Determine if exits are well lit & functioning.
13. Determine if the factory has adequate firefighting equipment (standard specified).
14. Determine if the factory provides adequate space for workers to perform their job in a safe manner (including factory layout).
15. Determine if machinery in the factory have appropriate safety measures/devices in place.
16. Determine if the factory provides PPE at no cost to workers.
17. Determine if any electrical hazards are present (standard specified).
18. Determine if any mechanical hazards are present (standard specified).
19. Determine if unrestricted drinking water is provided to workers.
20. Determine if the factory is well ventilated & maintained at a comfortable temperature.
21. Determine if the factory is well lit in production areas (standard specified).
22. Determine if noise levels in the factory are within limits (standard specified).
23. Determine if adequate & clean toilets are provided.
24. Determine if dining facilities are clean (if present).

25. Determine if the factory has proper disposal of trash (inside and outside the factory).

26. Review disposal of hazardous/combustible materials.

27. Review of building/structure for safety.

28. Review if the factory has a blood borne pathogen program.

The Health & Safety Super Category required auditors to be trained in procedures related to building, chemical, mechanical & electrical safety. The most common method for evaluating Health & Safety was through physical visits to factories through which visual evidence was captured to provide proof.

### 3. 4. 2 Labor Super Category

The Labor Super Category included questions related to labor relations, wages, contracts, and other related practices. The Labor Super Category includes eight SCA categories and 21 questions:

*Child Labor*: The corporation's policy required that no person below the age of 15 be employed in the factory (14 years if age where ILO guidelines are applied). This category included two questions.

1. To determine if the factory has processes designed to restrict recruitment of child labor.
2. To review if the factory has prescribed health checks and age verification for workers below the age of 18.

*Forced Labor*: The corporation's auditing guidelines explicitly called for prohibition of involuntary, indentured, or bonded labor. There was a single question in the auditing guidelines that examines the presence of forced labor. The process for evaluating this item consisted of reviewing documentation, steps to review documentation, and country specific guidelines regarding convict labor.

*Freedom of Association & Collective Bargaining*: The auditing of this SCA category was dependent on local laws. The corporation required that no employee be subject to harassment, intimidation, or retaliation for their efforts to associate or bargain collectively. There were three questions to examine this SCA category.

1. Determine if the factory communicates local and international laws related to Freedom of Association.
2. Examine if employees were subject to harassment, intimidation, or retaliation for their efforts to unionize.
3. Determine if the factory has a grievance redressal mechanism.

*Harassment or Abuse*: The factories engaging in business with the corporation were required to treat all associates with dignity and respect. This included not subjecting them to any form of corporal, physical, sexual, psychological, or verbal abuse. Auditors examined this SCA category using one question.

*Hours of Work*: All suppliers were expected to adhere to the specified maximum hours of work or the local legal limit (whichever is lesser). The factory was required inform employees of their overtime policy. The auditor used two questions to address to working hours practices in the factory:

1. Examine if the overtime hours in the factory do not regularly exceed the legal/corporation minimum
2. Examine whether all employees at a factory are provided a day off per week

*Non-Discrimination*: The SCA category for Non-Discrimination provides guidance for factories to avoid discrimination towards their employees and in matters related to hiring practices, benefits, advancement, termination, and retirement. Additionally, factories may not discriminate

against any person based on race, age, color, national origin, gender, religion, sexual orientation, disability, political opinion, or social or ethnic origin. The auditing manual provided for one question to examine this category.

*Wages & Benefits*: While no standard for "living wage" was specified, the auditing mechanism provided for evaluation of compensation packages, pay periods and benefits. Overall, there were nine questions in this category:

1. Provision to determine if workers are compensated fairly – at legal minimum wages applicable or at prevailing industry wages.
2. Provision to determine if the factory provides mandatory employee benefits and services.
3. Examine the overtime policy and rates of the factory. Verify compliance with local law.
4. Determine if the facility provides pay slips or similar written record of payroll for each pay period.
5. Determine if the factory does not utilize home employment
6. Examine if the frequency of pay meets legal requirements
7. Review the period for which the factory maintains payroll history and records (per legal provisions)
8. Determine if workers are provided adequate meal & rest breaks
9. Examine if factory utilizes temporary/seasonal labor in accordance with law

*Women's Rights*: The auditing manual contained a single question to address women's rights. In this SCA category, the auditors examine whether the factory provides equal opportunities for women. Specific practices related to reproductive rights, privacy and legal maternal benefits were also reviewed.

### 3. 4. 3 Legal & Environmental Super Category

The Legal and Environmental Super Category included the following SCA categories and questions:

*Environment*: The corporation's COC, TOE and the auditing manual provide detailed commitments to environmental stewardship. There was one question that examines the environment related practices in a factory. The auditors review permits for water discharge, chemical storage, and disposal of solid waste. The factory, if above a certain size, must have an onsite water treatment plant. The auditors may be required to carry out wastewater sampling for assessment by an independent laboratory. The manual also specified factory limits for wastewater discharge.

*Informed Workplace*: The informed workplace SCA category provided oversight related to communication by the factory to their employees. The method of communication can be oral, written or in other forms. The auditor determines compliance by interviewing workers and reviewing training logs.

*Legal compliance*: The Legal Compliance SCA category examines whether the factory is properly registered, licensed and permitted to perform their respective business activities. The auditor verifies documents related to factory licensing & permits, and the information of key personnel involved in the business. There were two questions in the auditing protocol that address this SCA category. Examining documentary evidence was the predominant method provided in the auditing protocol for this Super Category.

1) Determine if the factory is properly licensed, registered and permitted to perform current activities.

2) Determine if the factory maintains all relevant documents up to date and properly filled.

## 3. 6 Analytical Model

After examining the SCA categories and the questions, the researcher created a table using Excel which specified the SCA categories and audit questions for subsequent analysis. This file was designated as the mapping file and grouped individual audit questions to respective SCA categories and Super Categories. The researcher then used a tool called Power BI to connect this mapping to the auditing data stored in SDS. Using a computer programming language called DAX, the researcher encoded all individual responses in SDS. Pass responses were encoded as 0, and fail responses were encoded as 1. The researcher then created a many-to-one relationship between the encoded responses to the audit questions. In this case, many responses (corresponding to an audit question) were mapped to the respective SCA categories identified in the mapping file. This approach provided for the aggregation of question responses with the respective SCA categories and Super Categories. The data model is shown in Figure 3.3. This approach to construct a data model allows for no information loss while calculating the relevant metrics associated with the data. Such a data model mapped by a relationship of cardinality many-to-one allows for construction of measures that are contextual to a decision-making unit (DMU) (Myers et al, 2021). In our case, a DMU could be a Focal SCA category or a super category.

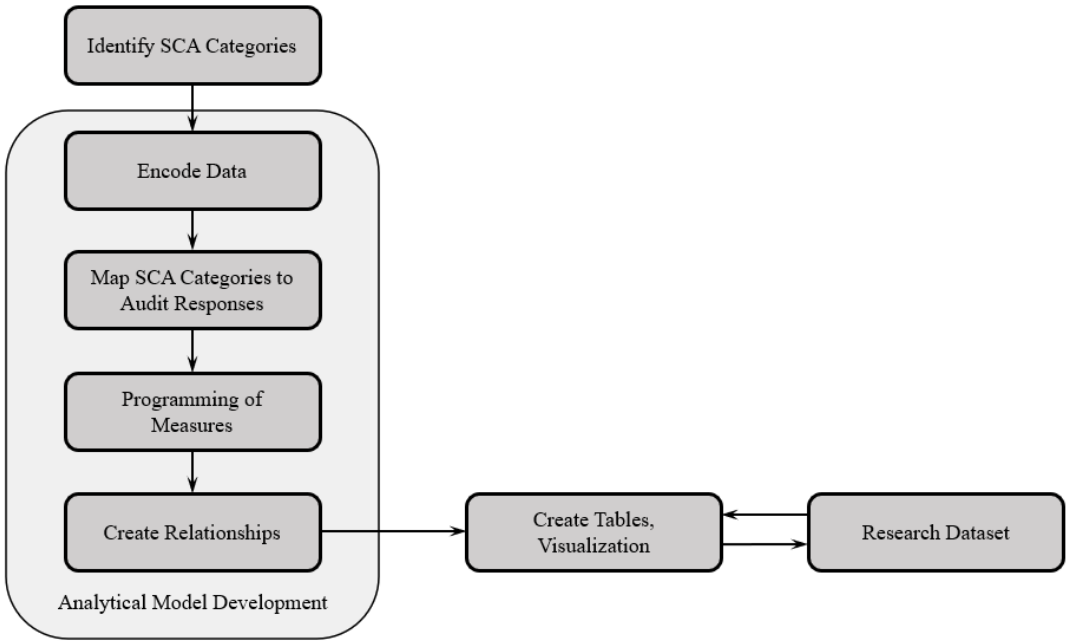



**Figure 3.3: Analytical Model Development**

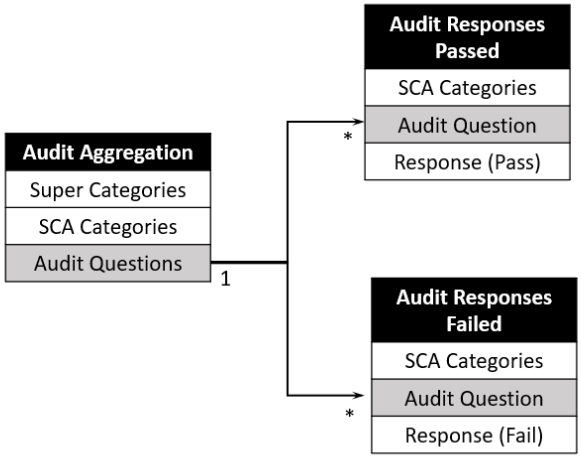



**Figure 3.4: Relationship Mapping within Analytical Model**

## 3. 7 Measures and Datasets

In order to detect CMV and measure its influence on various SCA categories, we construct a bounded, fractional metric *violation occurrence rate* (*O*) using the analytical model defined in section 3.4. The *O* metric is calculated using the formula below:

$$O = \frac{\Sigma\, N_v}{\Sigma\, Q_v}$$

where,

$O$ denotes *violation occurrence rate*

$\Sigma\, N_v$ denotes the total number of violations observed by the auditor for an aggregation category

$\Sigma\, Q_v$ denotes the total number of questions posed by the auditor for an aggregation category

and *v* can be a SCA category, super category, or all audits.

The *O* metric is bounded between the values of 0 and 1. A value of 0 indicates that the auditor has not reported any occurrence of a violation associated with the audit question. Similarly, a value of 1 indicates that the auditor has reported a violation occurrence on all audits for the corresponding audit question. Accordingly, a value of 0 would indicate that an auditor has "Passed" all questions corresponding to the audit item or question, and a value of 1 would indicate that the auditor has always marked the particular audit item as "Fail". In practice, the *O* metric for an auditor who has performed multiple assessments could be 0 but is unlikely to be 1. Within this dissertation, the *O metric* is referred also referred to as *O rate* or *violation rate* or *violation occurrence rate*.

To answer the research questions, four datasets were constructed using the analytical model. *Violation Occurrence Rate* (O) was the unit of measure used in all datasets. Auditors who

had conducted only one assessment were excluded from O metric calculation. All datasets were obtained from the SDS, and no further modifications were made to the data sources or data sets. The first dataset comprised of violation occurrence rates reported by auditors for all super categories. The dataset was designated DS1 and was used to analyze RO1. The second dataset (DS2) was comprised of violation occurrence rates reported by auditors for all Focal SCA Categories. This dataset was used to analyze the outcome for RO2. The third and fourth datasets contained the occurrence of rates of Focal SCA categories for the countries that were under study. These datasets were designated DS3 & DS4 respectively and were used to analyze the outcomes of RO3. In all the datasets, the row information in all datasets contained the violation occurrence rates reported by anonymized auditors, while the column information corresponded to variables of super categories or the Focal SCA categories.

## 3. 8 Analysis steps & plan

In this section, we provide an explanation of the statistical tools used to identify auditor bias.

### 3.8.1 Correlation matrix

According to Richardson et al (2009) and Williams et al (2010), there exist multiple methods to detect and measure the presence of Common Method Variance (CMV). For example, Kline et al (2000) use *bivariate correlations* to examine the presence of CMV in reporting social desirability. One common statistical test used for bivariate correlations is the Pearson Correlation coefficient. In the first step of the analysis, we compute the correlation matrix for the Super Categories and Focal SCA categories in DS1, DS2, DS3 and DS4. According to the Kline et al (2000), the examination of the correlations does not provide a definitive indication of CMV presence.

### 3.8.2 Harman's single factor test

According to Fuller et al (2016), the most commonly used method to detect the presence of CMV is *Harman's Single Factor Test*. In this technique all variables in the study are loaded into one factor using Exploratory Factor Analysis. The unrotated factor solution is then examined to determine the number of factors that are necessary to account for the majority of variance in the variables. If substantial common method variance is present, then 1) a single factor will emerge from the factor analysis or 2) one general factor will account for the majority of the covariance among the measures. However, Williams et al (2010) state that, while *Harman's test* can be useful to detect CMV, it may not be able to detect CMV on all occasions. In addition, *Harman's single factor test* also cannot be used to directly measure CMV, hence researchers often have to utilize supplementary techniques to accomplish this. Despite limitations, Harman's test remains widely used test to detect CMV. Williams et al (2010) go further and propose an additional technique called "*CFA marker variable method*" in order to measure CMV. However, the authors also recommend detecting CMV using Harman's single factor test before the application of CFA marker variable method.

### 3.8.3 CFA Marker Variable Method

In this study, we use a modified template of *CFA marker variable method* as discussed by Williams et al (2010) to measure auditor bias. In this template, we use the Confirmatory Factor Analysis (CFA) technique using Structured Equation Modeling (SEM) to measure latent variables. To measure CMV, besides the substantive variables in the equation, we use additional variables designated as markers. The advantage of using marker variables with SEM allows for many advantages such as

1) Providing a statistical test of bias due to marker variable effects.

2) Provides a baseline model for comparison.

3) Allows test of assumptions between constrained and unconstrained factors, while controlling for random measurement error.

The analysis plan for this study utilized 4 step confirmatory factor analysis model (CFA model) developed using SEM technique. Multiple CFA models were built, and relevant measures of fit were obtained. The following model fit measures are used for interpretation 1) Comparative Fit Index (CFI) 2) Tucker – Lewis Index (TLI) 3) Root Mean Square Approximation (RMSEA) and 4) Degrees of Freedom. Since our goal is to measure CMV, and not ascertain model fit, the fit measures are only used for comparison purposes.

In step 1 of the test plan, a CFA model is built with default factor loadings. In this model, the factor loadings that are used for analysis i.e., the Super Categories or the Focal SCA Categories are referred to as substantive variables. In addition, the marker variables are loaded into the model using a separate factor. These are referred to as Method Factor Loadings. There are no correlations specified for any substantive or method variables. This model is referred to as the Priming model (Model 0).

In step 2, two correlations between the substantive variables and method variables are forced to 0, while the correlations within the substantive variables are retained. This model is referred to as the Baseline model (Model 1).

In step 3, two additional models are specified. In the third model the method factor loadings are added back into the model assuming these factors all have equal values. This model is designated as Constrained model (Model 3). In the final model, all method factor loadings are added back into the model, except that all factors are unconstrained. This

model is referred to as Unconstrained model (Model 4). The examination of these models allows to determine the sensitivity of results thereby measuring CMV.

Overall, the priming model is used to identify substantive and method factor loadings. The Baseline model is used to determine zero method effects, while the Constrained model is used to estimate equal method effects and the Unconstrained model is used to determine unequal or variable method effects. If the Constrained or Unrestricted model fits better than the Baseline model, we infer that CMV is present. If the Unrestricted model fits better than Constrained model, we infer that CMV is unequal across factors. Finally, the CMV is calculated using Williams – Hartman - Cavazotte method (2010).

The operation of Williams – Hartman – Cavazotte formula is based on the substantive ($\alpha_i$) and marker ($\delta_i$) factor loadings along with the corresponding marker variances ($\theta_i$) measured from the constrained or unconstrained model, for $i^{th}$ Focal SCA category. In the priming model, the measured substantive latent variables are allowed to correlate with marker variables. This is denoted by $m_j$. Where, m is the correlation between the $j^{\text{th}}$ latent variable pair. To measure the constrained model, all marker loadings ($\delta_i$) are set to be equal, while in the unconstrained loading, they are free. Only standardized loadings are used for measures. The CFA measurement model is outlined in table 3.2 below.

**Table 3.2: CFA marker variable model parameters**

| CFA model name | Parameters |
|---|---|
| Priming model | $\vartheta_i = 0$<br><br>All other parameters are freely estimated |
| Baseline model | $m_i = 0$<br><br>$\vartheta i = 0$<br><br>$\delta_i$ from priming model |
| Constrained model | $m_i = 0$<br><br>$\vartheta_i = a$<br><br>$\delta_i$ from priming model |
| Unconstrained model | $m_i = 0$<br><br>$\vartheta_i$ = free<br><br>$\delta_i$ from priming model |

CMV is then expressed in terms of reliability measures of the measured substantiative and marker loadings, measured as noted below

$$R_t = \frac{(\alpha^2 + \delta^2)}{(\alpha^2 + \delta^2 + \theta)}$$

$$R_m = \frac{\delta^2}{(\alpha^2 + \delta^2 + \theta)}$$

$$C_i = \frac{R_m}{R_t}$$

Where,

$R_t$ is the total reliability of all substantive and marker factor loadings,

$R_m$ is the method reliability (from marker loadings)

CMV is then expressed as the ratio of method reliability to total variability ($C_i$).

### 3.8.4 Analysis plan

The analysis plan began with the examination of summary statistics of the research datasets. Our first research objective was to determine whether auditor bias is present. To do so, we started by comparing the Pearson Correlation coefficient of occurrence rates in DS1 and DS2. We then proceeded detect if CMV was present in DS1 and DS2 using Harman's Single Factor test, followed by measuring CMV using CFA marker variable method.

In RO2, we aim to understand the variability of auditor bias, by analyzing the difference in occurrence rates determined by auditors between the Focal SCA Categories. To do so will require understanding the correlations between various Focal SCA Categories. Further to measure CMV, we utilized the results from the CFA marker variable method to calculate auditor bias for each focal SCA category. Additionally, to conclude if the relationship between the Super Categories and Focal SCA Categories are parsimonious, we performed Exploratory Factor Analysis (EFA) using DS2.

To examine RO3, the SDS datasets were filtered based on different countries to be examined. The rules governing the filtering are discussed in Chapter 4. The *CFA Marker Variable method* will be used to ascertain CMV comparison between countries.

### 3.8.5 Software and tools used

Microsoft Power BI was used to specify the analytical model on SDS. The research datasets were then downloaded from there as CSV files. Overall, 4 research datasets were constructed viz. DS1, DS2, DS3 and DS4. JMP Pro 16 was used to obtain Pearson Correlation Coefficients and conduct Harman's Single Factor test using EFA. R 4.2 with Lavaan Package was used to implement CFA marker variable method. The software code used for R is shown in Appendix iv, v & vi. Microsoft Excel was used for results collection and interpretation.

# CHAPTER 4

## Data Analysis and Results

This chapter details the results and conclusions of various analysis and statistical tests described in the Methodology section. The results are presented in this chapter are in the order given in the analysis plan. Conclusions specific to the research objectives are discussed in the next chapter. We begin by describing the data captured in SDS, followed by analyzing the summary statistics of all research datasets. In the next section we proceed to analyze the super categories, followed by Focal SCA categories and country level data. The results from the comparative model analysis of the EFA and CFA models are discussed next. In the last section supplemental qualitative analysis related to audit methods is also covered. The sections discussed in this chapter are shown below.

4. 1 Data description

4. 2 Aggregated auditor data summary

4. 3 Violation Summary

4. 4 Research datasets & Variables

4. 5 Super Category analysis

4. 6 Focal SCA Category analysis

4. 7 Country specific analysis

4. 8 Latent variable measurements (EFA Vs CFA Comparison)

4. 9 Method Descriptions

## 4. 1 Data description

To construct the required datasets, a sample data source (SDS) was set up containing audit information of the data providing corporation. We developed SQL queries to obtain information regarding all SCAs conducted by the corporations between July 2015 to July 2019. Due to the large volume of data, the queries were run iteratively for 1-month periods to obtain the data. The raw data was then stored in a database table. The column descriptions of the table are shown in table 4.1.

Overall, SDS comprised of 15860 unique assessments/audits, conducted across 5466 factories over a 5-year period across 80 different countries. All audits were carried out using one questionnaire, which had 32 different response types at 65 responses per assessment. Out of 65 responses for every assessment, only 56 were considered for formulating research datasets. These responses correspond to only those that had been marked Pass or Fail by auditors. The other responses were not considered for analysis as they contained other information pertaining to audit scheduling and factory data. The audits were conducted by 80 unique auditors. The overall data summary is shown in the table 4.2.

The largest number of factories were located in China, followed by USA, Vietnam and India. On average, three assessments had been conducted in each of the factories across all countries. The top 10 countries that had most assessments per factory were France, Moldova, Macedonia, Ecuador, Guatemala, Bangladesh, Cambodia, India, Indonesia and Vietnam. The average number of assessments in these countries ranged from 3.6 in Vietnam to 5 for France. Similarly, the largest number of auditors had conducted audits in China, followed by USA, Taiwan, Mexico, and Vietnam.

**Table 4.1: Column description of SDS data table**

| Column Name | Description |
|---|---|
| Factory ID | Identifier for factory information |
| Assessment ID | Identifier for Assessment ID |
| Assessment Date | Date on which the audit was undertaken |
| Assessment Monitor | Deidentified auditor name |
| Questionnaire | Type of questionnaire used in audit |
| Issue Type | Name of the COC issue associated with the audit question (Focal SCA category) |
| Question | Audit question/ Audit item |
| Response type | Type of response associated with the audit question |
| Response | Response associated with audit question |
| Assessment Status | Status of Assessment (complete/incomplete) |

Overall, SDS comprised of 15860 unique assessments/audits, conducted across 5466 factories over a 5-year period across 80 different countries. All audits were carried out using one questionnaire, which had 32 different response types at 65 responses per assessment. Out of 65 responses for every assessment, only 56 were considered for formulating research datasets. These responses correspond to only those that had been marked Pass or Fail by auditors. The other responses were not considered for analysis as they contained other information pertaining

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**Table 4.2: Distribution of audits conducted by an auditor**

| Data Description | # Of data points |
|---|---|
| Number of individual assessments | 15860 |
| Number of Unique Factories | 5466 |
| Time Period | July 2015 to July 2019 |
| Number of unique auditors | 80 |
| Number of countries where assessments were conducted | 80 |

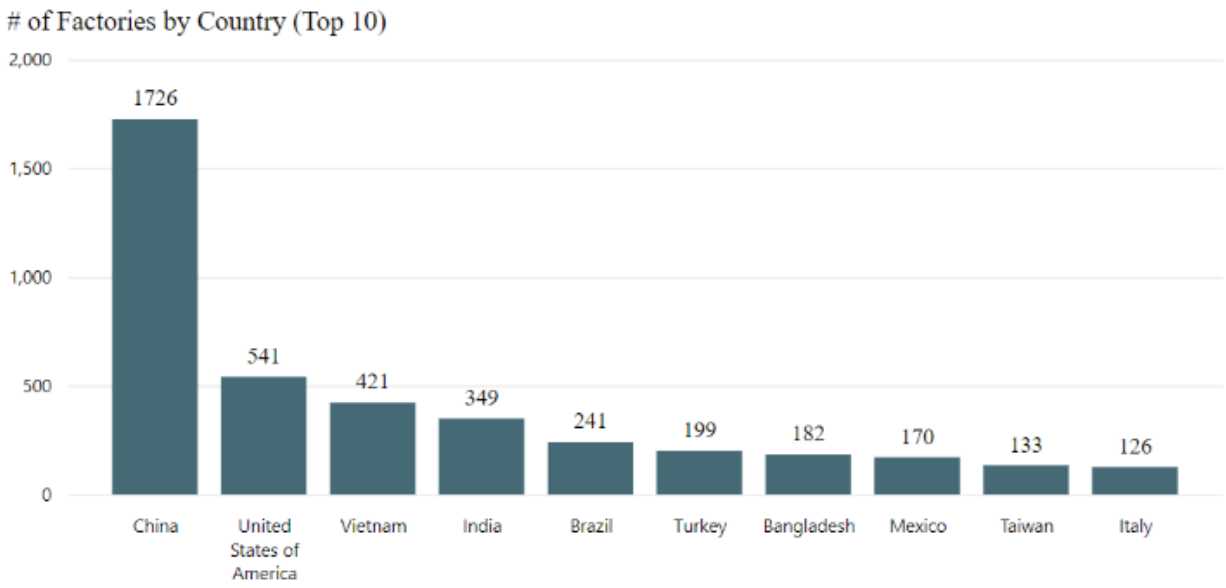


**Figure 4.1: # of Factories by country (Top 10)**

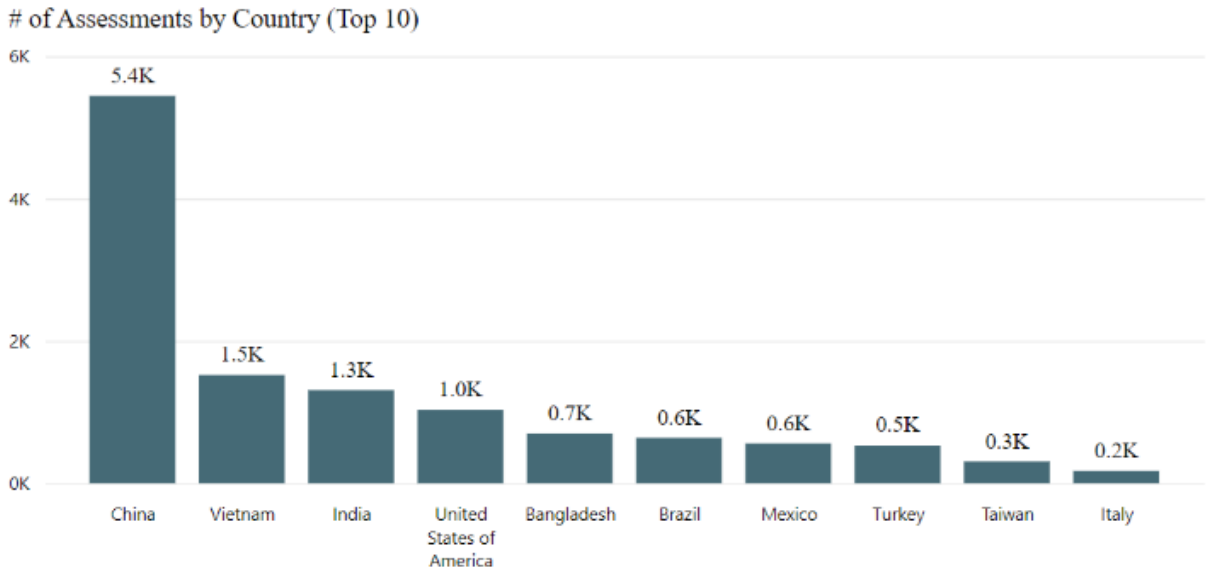


**Figure 4.2: Number of assessments by country (Top 10)**

## 4. 2 Aggregated auditor data summary

To begin understanding auditor bias, we need to understand the relationship between number of auditors and the number of countries and factories where they had performed assessments.

Needless to say, China with the greatest number of factories and assessments also had the greatest number of auditors. This was followed by USA, which also had the second largest number of factories and auditors. Taiwan, despite not having a large number of factories, had the third largest number of auditors. These metrics suggested that the number of auditors deployed by the corporation could be dependent on both the number of assessments and the number of factories in a country. In all, auditors in China auditors performed more assessments and audited more factories per capita than auditors in any other country. For instance, in China, on average an auditor would have performed 127 assessments in 41 factories over the five-year period. This was followed by India, where an auditor would have performed 101 assessments in 27 factories, on average. It was further observed that was a compact relationship between the top 12 countries in terms of average assessments and the average number of factories visited by an auditor. This information is shown in table 4.3.

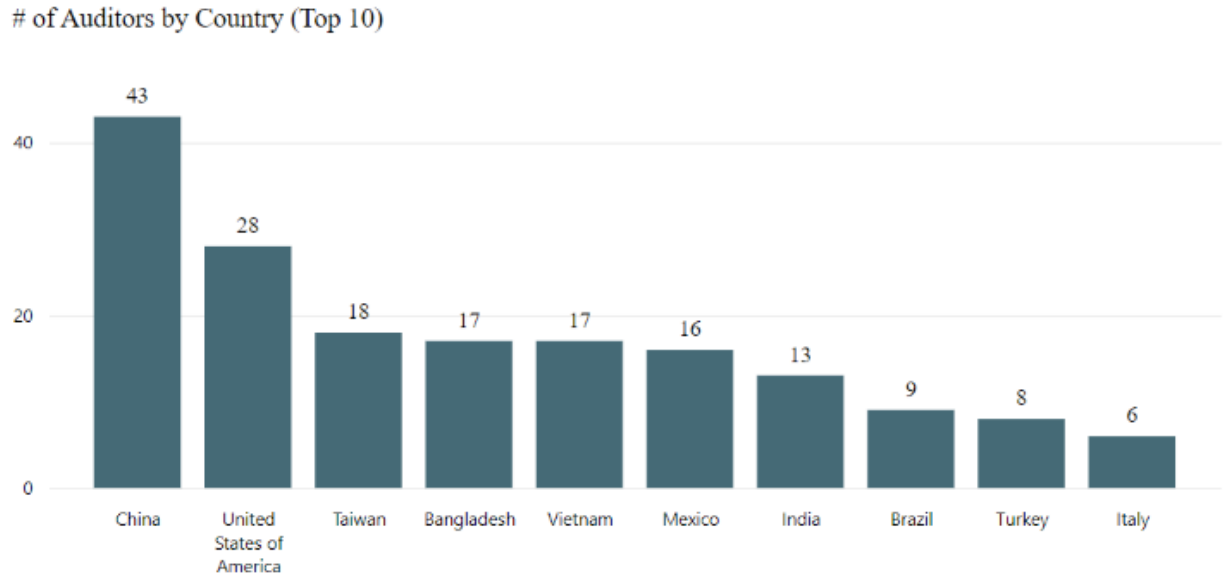


**Figure 4.3: Number of auditors by country (Top 10)**

**Table 4.3: Average assessments performed, and factories visited by an auditor (Top 12 countries)**

| Country | Average number of factories audited by an auditor | Average number of assessments performed by an auditor |
|---|---|---|
| China | 41 | 127 |
| India | 27 | 101 |
| Brazil | 27 | 71 |
| Turkey | 25 | 66 |
| Vietnam | 25 | 89 |
| Italy | 21 | 28 |
| United States of America | 20 | 37 |
| El Salvador | 14 | 47 |
| Thailand | 12 | 40 |
| Bangladesh | 11 | 41 |
| Mexico | 11 | 35 |

Since the focus of our research questions is auditor bias, auditors who had audited in only one factory were excluded from the analysis. It was also identified that 841 audits did not contain auditor information. Overall, 970 audits were excluded from the analytical model as they did not contain auditor information, were incomplete or had auditors who had conducted only one assessment. The data used for constructing the research datasets contained 14890 assessments, with 62 unique auditors. Within the modified dataset, the total number of audits conducted by an auditor ranged from 2 to 772. The distribution of audits conducted by auditors and the distribution of countries by auditor count is shown in tables 4.4 and 4.5.

**Table 4.4: Distribution of audits conducted by an auditor**

| # Of audits (range) | # Of auditors |
|---|---|
| 2 to 50 audits | 19 |
| 51 to 100 audits | 7 |
| > 100 audits | 36 |
| **Total** | **62** |

**Table 4.5: Distribution of number of countries assessments performed by an auditor**

| # Of countries (range) | # Of auditors |
|---|---|
| 1 to 10 countries | 46 |
| 11 to 20 countries | 11 |
| > 20 countries | 5 |
| **Total** | **62** |

## 4. 3 Violation summary

During an assessment, an auditor would note a violation or noncompliance observed in a factory by marking the appropriate audit item as "Fail." In all, there were 102,505 unique violations, with an average of 6.9 violations per assessment. Also included among the violations were issue categories that are not part of this research. These categories were excluded from the research datasets. For the focal SCA categories considered, the auditors had reported 96, 219

violations. The details of number of violations reported by focal SCA category are shown in table 4.6.

**Table 4.6: Violation and Occurrence rate summary**

| Super Category | Focal SCA Category | Number of violations | Violation Occurrence Rate |
|---|---|---|---|
| Health & Safety | Health and Safety | 65566 | 0.21 |
| **Health & Safety Total** | | **65566** | **0.21** |
| Labor | Child Labor | 711 | 0.03 |
| | Forced Labor | 407 | 0.04 |
| | Freedom of Association and Collective Bargaining | 1557 | 0.05 |
| | Harassment and Abuse | 591 | 0.09 |
| | Hours of Work | 7090 | 0.33 |
| | Non - Discrimination | 296 | 0.04 |
| | Wages and Benefits | 11694 | 0.12 |
| | Women's rights | 917 | 0.13 |
| **Labor Total** | | **23263** | **0.11** |
| Legal & Environmental | Environment | 2669 | 0.24 |
| | Informed Workplace | 423 | 0.06 |
| | Legal Compliance | 4298 | 0.13 |
| **Legal & Environmental Total** | | **7390** | **0.15** |

The Health & Safety super category had the greatest number of violations, followed by Labor and Legal & Environmental. This was expected, as the Health & Safety super category also had the largest number of questions. Within the Labor super category, the Wages & Benefits SCA category had the greatest number of violations at 11694, while Non-Discrimination was the lowest with only 296 violations. For the Legal & Environmental super category, a total of 7390 violations were reported, with the Legal Compliance having the greatest number of violations and Informed Workplace the lowest.

In order to calculate the occurrence rates for different auditors, an analytical model was developed using SDS. In the analytical model, sub-tables were constructed with one containing all responses marked "Fail," and another table containing all responses marked both "Pass" and "Fail." This analytical model was constructed to facilitate calculation of the *Violation Occurrence Rate (O) metric*. The violation occurrence rates for various SCA categories are shown in table 4.6. Once the analytical model was developed, the data was transformed to obtain research datasets.

## 4. 4 Research Dataset and Variables

As discussed in the previous chapter, a total of 4 datasets were developed to evaluate the research objectives. The first research dataset DS1, was used to evaluate RO1 and RO2 at super category level of aggregation. The second dataset DS2, was used to evaluate RO1 & RO2 at Focal SCA category level. This was done to distinguish the levels of auditor bias that may occur at various levels of focus of an audit, by an auditor. Finally, DS3 and DS4 datasets were constructed in order to observe the differences in auditor bias that may occur in audits happening in different countries. Though the data from SDS had 80 different countries, only two countries (China & USA) had sufficiently unique number of auditors to perform this evaluation.

**Table 4.7: Dataset descriptions**

| Dataset name | Purpose |
|---|---|
| DS1 | Evaluate RO1 & RO2 at super category level |
| DS2 | Evaluate RQ2 at Focal SCA category level |
| DS3 | Evaluate RO3 objectives (USA) |
| DS4 | Evaluate RO3 objectives (China) |

In all datasets, the row information corresponded to the occurrence rates reported by the 62 auditors being analyzed. For DS1, the column headers were super categories, and it was Focal SCA categories for other datasets. The structure of the datasets and the variable names are shown in the tables below.

**Table 4.8: Variable descriptions**

| Variable Name | Description | Dataset(s) |
|---|---|---|
| *Aud* | Auditor | DS1, DS2, DS3, DS4 |
| *HS* | Health & Safety Super Category (O metric) | DS1 |
| *LA* | Labor Super Category (O metric) | DS1 |
| *EL* | Labor & Environment Super Category (O metric) | DS1 |
| *CL* | Child Labor (O metric) | DS2, DS3, DS4 |
| *Env* | Environment (O metric) | DS2, DS3, DS4 |
| *FL* | Forced Labor (O metric) | DS2, DS3, DS4 |
| *FoA* | Freedom of Association (O metric) | DS2, DS3, DS4 |

**Table 4.8 (continued): Variable descriptions**

| Variable Name | Description | Dataset(s) |
|---|---|---|
| *HA* | Harassment & Abuse (O metric) | DS2, DS3, DS4 |
| *HS1* | Health & Safety (O metric) | DS2, DS3, DS4 |
| *HW* | Hours of Work (O metric) | DS2, DS3, DS4 |
| *IW* | Informed Workplace (O metric) | DS2, DS3, DS4 |
| *LC* | Legal Compliance (O metric) | DS2, DS3, DS4 |
| *ND* | Non - Discrimination (O metric) | DS2, DS3, DS4 |
| *WB* | Wages & Benefits (O metric) | DS2, DS3, DS4 |
| *WR* | Women's Rights (O metric) | DS2, DS3, DS4 |
| *MFC* | Marker Variable 1 | DS2, DS3, DS4 |
| *MMC* | Marker Variable 2 | DS2, DS3, DS4 |
| *MSC* | Marker Variable 3 | DS2, DS3, DS4 |
| *MDO* | Marker Variable 4 | DS2, DS3, DS4 |

## 4. 5 Data Quality

The corporation that provided us the data uses an internal audit checking processes to ensure that the data is clean. These steps include

1) Using an audit clearing process to ensure all audits conform to the code of conduct.
2) Using a flag to determine the completion status of an audit
3) Obtaining explanation for non-conformities or violations noted in an audit
4) Using a standard scale for rating severity of violations

For the analysis used in this study, only audits that were completed and cleared were used. Despite these procedures, it was found 841 audits out of 15860 had no auditor or country information. 13 audits were labeled “test audits”. These audits were not excluded from the study. The final dataset that was examined had 14,890 unique assessments.

## 4. 6 Super Category Level Analysis

From the analytical model, it was determined that that O metrics for were 0.21 for Health & Safety, 0.11 for Labor and 0.15 for Legal & Environmental super categories. This demonstrated that Health & Safety violations are identified more frequently, followed by Legal & Environmental and Labor violations.

The analysis plan for super category level began followed the steps below:

5) Examine the summary statistics and Pearson’s correlations between super categories
6) Perform Harman’s Single Factor test using EFA using DS1

### 4.5.1 Summary Statistics

In this section, we examined the mean, standard deviation and range of violation occurrence rates reported by 62 auditors in DS1. The results are shown in table 4.9.

**Table 4.9: Summary statistics for super categories**

| ***Super Category*** | *Mean* | *Std Dev* | *Range* | *Minimum* | *Maximum* | *N* |
|---|---|---|---|---|---|---|
| **Health & Safety** | *0.2056* | *0.0762* | *0.3500* | *0.0400* | *0.3900* | *62.0000* |
| **Labor** | *0.0989* | *0.0617* | *0.2400* | *0.0000* | *0.2400* | *62.0000* |
| **Legal & Environmental** | *0.1281* | *0.0755* | *0.3400* | *0.0000* | *0.3400* | *62.0000* |

**Table 4.10: Difference in means for super categories**

| ***Focal SCA Category*** | *Sample Mean* | *Audit Mean* | *Abs Difference* |
|---|---|---|---|
| Health & Safety | 0.2056 | 0.214 | 0.0084 |
| Labor | 0.0989 | 0.1143 | 0.0154 |
| Legal & Environmental | 0.1281 | 0.1472 | 0.0191 |

*Health & Safety*: The mean *O* for Health & Safety super category was 0.21, which was the same as the mean for all SDS. All auditors had reported violations in this category. The occurrence rates for this category ranged from 0.04 to 0.39, with a standard deviation of 0.0762. The values were normally distributed with one mode, which was equal to the mean. 50% of auditors had *O* metrics between 0.15 and 0.25. Summary analysis indicates that there is no bias in Health & Safety super category since the means are same.

*Labor*: The occurrence rates of Labor super category ranged from 0 to 0.24, with a mean of 0.10 and standard deviation of 0.0617. The occurrence rates for this super category were the narrowest among all super categories, indicating auditor observations may be similar. The distribution of the values for this super category was tri-modal, with peaks at 0.05, 0.1 and 0.15. 27% of auditors had *O* metrics between 0.05 and 0.075, while 15% of auditors had O metrics between 0.15 and 0.175. Two thirds of auditors had O metrics lowers than median. These measures indicate that O metrics for this super category may be biased.

*Legal and Environmental*: The occurrence rates for this super category were spread between 0 and 0.34. The mean occurrence rate was 0.13 with a standard deviation of 0.0755. The distribution was unimodal, with a median of 0.125. A cumulative of 83% of auditor O rates were below 0.2, suggesting leniency effects among auditors reporting issues in this super category.

The distribution of O metrics for super categories are shown in Appendix (ii). Analyzing the summary statistics, it can be observed that among the super categories Legal & Environmental category showed the greatest bias, followed by Labor. There was no bias measured in Health & Safety. It should be noted here that, while summary statistics provide a measure of bias within the super-categories, they are not a measure of CMV or auditor bias.

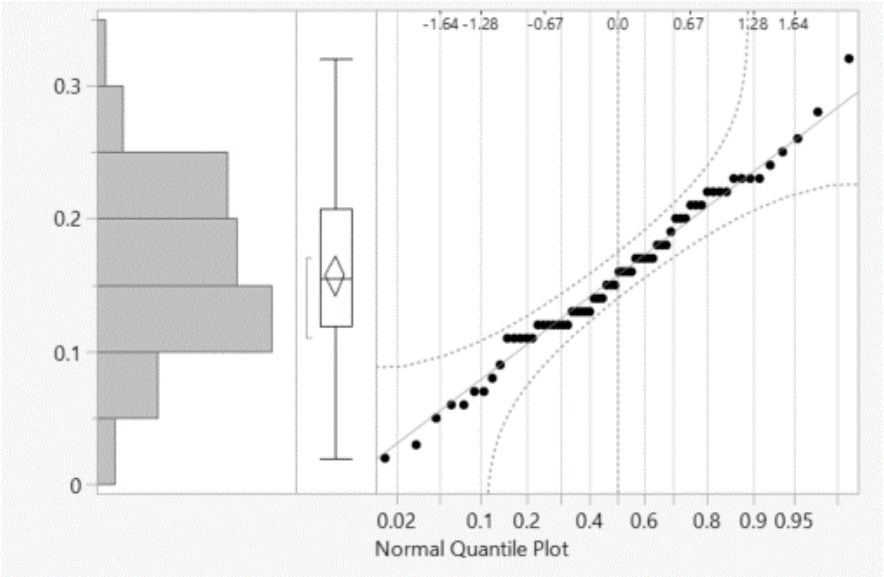


**Figure 4.4: Distribution of O-rate for all auditors**

### 4.5.2 Super Category Correlations

Further measurement of CMV required examining the correlations between super categories. It must be noted that high correlations between the values may indicate the presence of CMV. However, the correlation test is not a conclusive measure of CMV (Williams et al, 2010). The examination of correlations between super categories showed sufficiently high values that indicated the presence of CMV. The Pearson's Correlation coefficients measured for super category O rates is shown in the table below.

**Table 4.11: Super Category correlations**

| Correlations | | | |
|---|---|---|---|
| | **HS** | **LA** | **EL** |
| **HS** | 1 | | |
| **LA** | 0.5565 | 1 | |
| **EL** | 0.5658 | 0.5543 | 1 |
| The correlations are estimated by Row-wise method. | | | |

### 4.5.3 Harman's test for super categories

According to Aguirre-Urreta & Hu (2019), checking whether the first extracted factor explains more than 50 percent of the variance in the variables can be taken to be evidence that substantive CMV is present in the sample. However, this test does not detect the presence of a general factor and the observed factor may not necessarily be taken as a measure of CMV.

In this case, the results of EFA indicated the emergence of one latent factor could account for 70.592% of the variance of observed factors. The factor loading method used was Principal axis, with communality measured by principal components. In observing the unrotated factor loadings, it was found that the latent factor loadings were across all measured factors indicating all of them could be the source of CMV. The corresponding factor loadings are shown in table 4.11. This analysis also indicates the shortcoming of Harman's test, where it can be used to detect, but not measure CMV (Aguirre-Urreta & Hu, 2019; Williams et al, 2010). Accordingly, we conclude that CMV is present among O rates at super category level.

**Table 4.12: EFA Factor loadings from Harman's test for super categories**

| *Unrotated Factor Loading* | | | *Variance Explained by Each Factor* | | | |
|---|---|---|---|---|---|---|
| | **Factor 1** | | **Factor** | **Variance** | **Percent** | **Cum Percent** |
| HS | 0.8424625 | | Factor 1 | 2.1178 | 70.592 | 70.592 |
| EL | 0.8414083 | | | | | |
| LA | 0.8366902 | | | | | |

### 4.5.4 CFA Marker Variable analysis for super categories

CMV measurement using CFA marker variable technique involved development of 4 models for each super category. In this analysis, the corresponding focal SCA category is loaded on to the corresponding super category in a separate model, and along with the marker variables. The marker variables were kept the same for all models for consistent measurement of method effects. In all cases, the priming model was generated first to ascertain the working of the CFA model. In this model, the Marker variable is allowed to correlate with one super category at a time. This is shown in figures 4.5, 4.6, and 4.7.

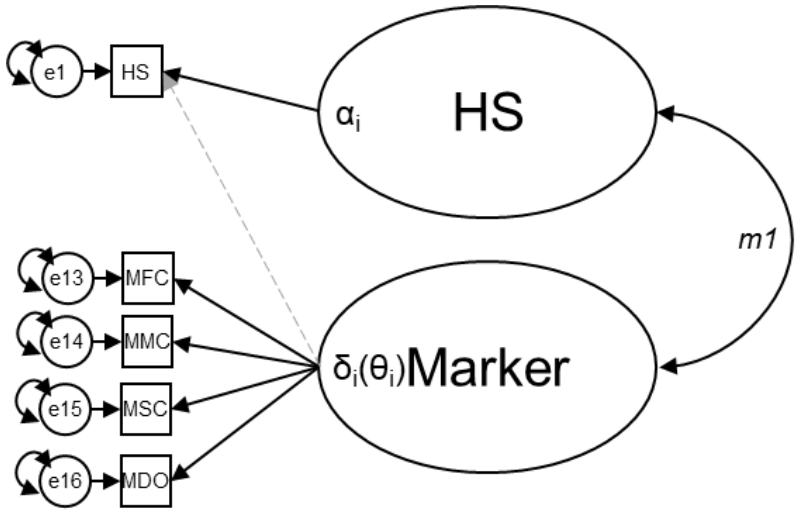


**Figure 4.5: Priming model for Health & Safety super category**

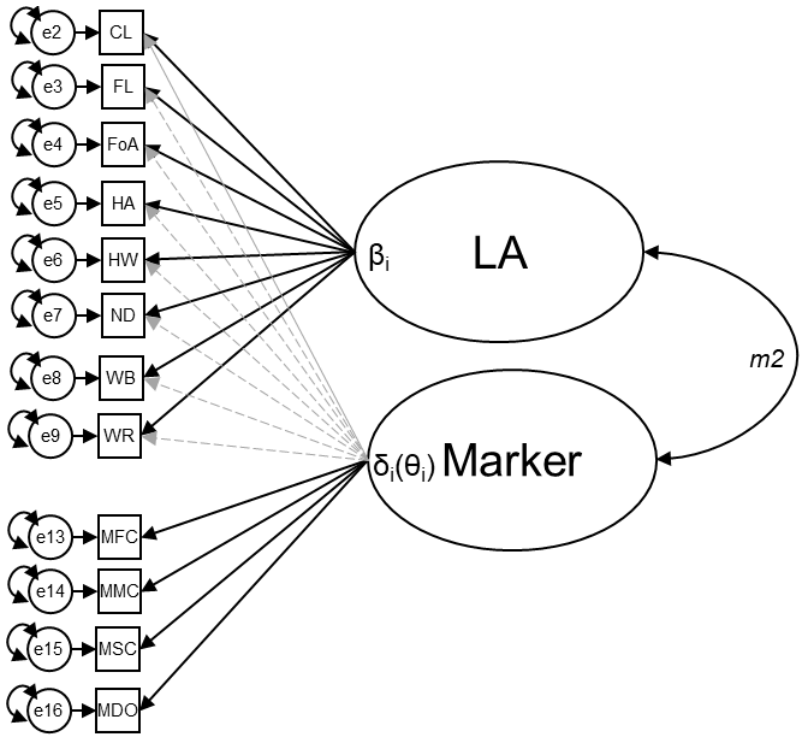


**Figure 4.6: Priming model for Labor super category**

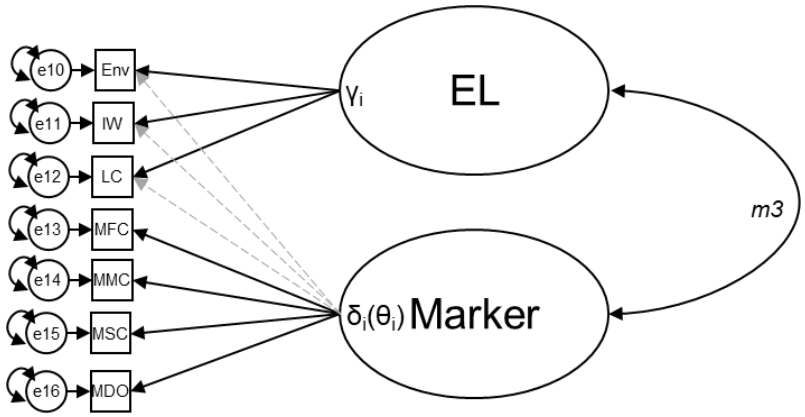


**Figure 4.7: Priming model for Legal & Environmental super category**

After measuring the factor loadings from the priming model, further models are run by varying the marker loadings to measure method effects. These models are designated as baseline,

constrained and unconstrained models. A total of 12 CFA models were constructed to evaluate CMV for super categories. These models were designated numbers 6 through 17.

These models are collectively designated as measurement models, shown in figures 4.8, 4.9 and 4.10 below.

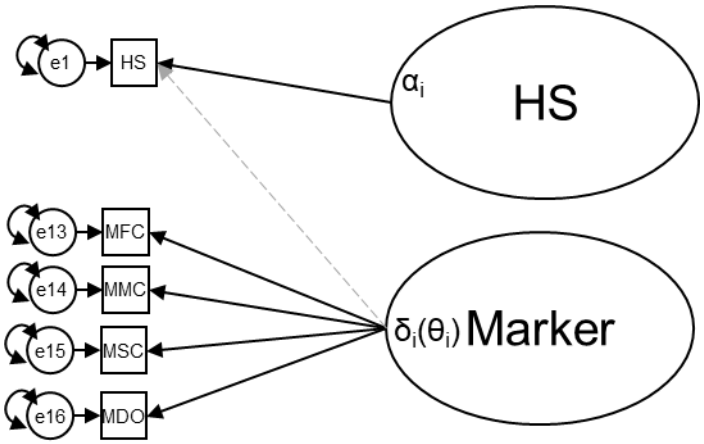


**Figure 4.8: Measurement model for Health & Safety super category**

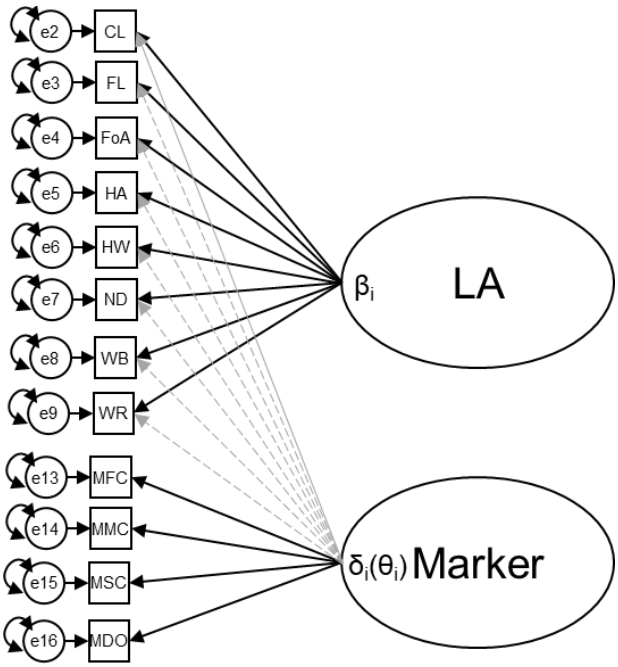


**Figure 4.9: Measurement model for Labor super category**

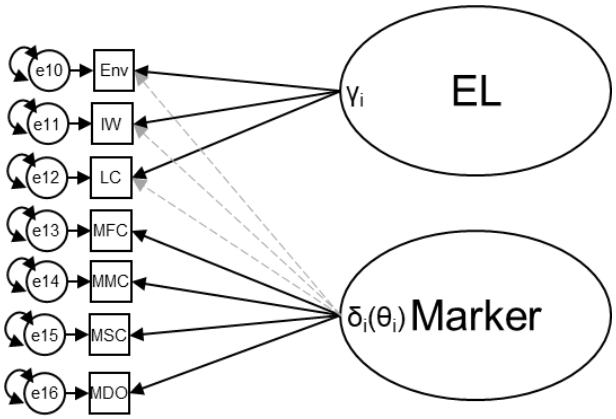


**Figure 4.10: Measurement model for Legal & Environmental super category**

In all cases of CFA model run, the number of parameters required by constrained & unconstrained models were more than the baseline models. This corroborated with the reduction in degrees of freedom, which were lesser for constrained and unconstrained models than the baseline model. A complete examination of CFA models involved examining their fit indices namely the CLI, TLI and RMSEA values. While the rule of thumb states that for models deemed "good fit," CLI and TLI indices have to be above 0.9 and RMSEA below 0.05, these constraints need not be applied to measure CMV (Williams et al, 2010) as the measures themselves are used only for model comparison. All super category level CFA models however showed sufficiently high fit indices, above the rule of thumb. The values for super category level CFA model and their fit measurements are shown in table 4.12, 4.13 and 4.14.

Based on examination of fit indices, the constrained model was deemed to be the best fit for Health & Safety super category. This indicates that CMV is present for this super category, and it has equal effects on all substantive measure part of this super category. Further insight for Health & Safety super category could not be obtained as there was only one substantive measure (Focal SCA Category) within this category. For the Labor and Legal & Environmental super

categories, unconstrained CFA models were found to fit the best. So, we concluded that CMV is present in all super categories, and it has unequal effects on the substantive variables.

We employed Williams – Hartman – Cavazotte formula to measure CMV for the super categories. Standardized loadings from *model 8* were used for Health & Safety. For Labor, standardized loadings from *model 13* were used, while for Legal & Environmental, *model 17* was used. It was found that CMV accounted for less than 1% of variance in the reliability of Health & Safety super category, 10% of variance in the reliability of Labor super category and 1.3% of variance in the reliability of Legal & Environmental super category, when the super categories are measured separately in audits.

**Table 4.13: CFA model fit measurements for Health & Safety super category**

| ***Model #*** | ***Name*** | ***# Params*** | ***# Of obs*** | ***Test Statistic*** | ***dF*** | ***CFI*** | ***TLI*** | ***RMSEA*** | ***Lower CI*** | ***Upper CI*** | ***SRMR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | *CFA HS* | 13 | 62 | 7.776 | 2 | 0.91 | 0.55 | 0.216 | 0.072 | 0.385 | 0.058 |
| 7 | *Baseline HS* | 8 | 62 | 17.056 | 7 | 0.843 | 0.776 | 0.152 | 0.06 | 0.246 | 0.16 |
| **8** | ***Constrained HS*** | **9** | **62** | **7.776** | **6** | **0.972** | **0.954** | **0.069** | **0** | **0.189** | **0.058** |
| 9 | *Unconstrained HS* | 9 | 62 | 7.776 | 6 | 0.972 | 0.954 | 0.069 | 0 | 0.189 | 0.058 |

**Table 4.14: CFA model fit measurements for Labor super category**

| ***Model #*** | ***Name*** | ***# Params*** | ***# Of obs*** | ***Test Statistic*** | ***dF*** | ***CFI*** | ***TLI*** | ***RMSEA*** | ***Lower CI*** | ***Upper CI*** | ***SRMR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 10 | *CFA LA* | 27 | 62 | 253.48 | 51 | 0.518 | 0.377 | 0.253 | 0.222 | 0.285 | 0.247 |
| 11 | *Baseline LA* | 22 | 62 | 253.496 | 56 | 0.53 | 0.446 | 0.239 | 0.209 | 0.269 | 0.247 |
| 12 | *Constrained LA* | 30 | 62 | 222.54 | 55 | 0.601 | 0.522 | 0.222 | 0.192 | 0.252 | 0.501 |
| **13** | ***Unconstrained LA*** | **30** | **62** | **83.437** | **48** | **0.916** | **0.884** | **0.109** | **0.068** | **0.148** | **0.073** |

**Table 4.15: CFA model fit measurements for Legal & Environmental super category**

| ***Model #*** | ***Name*** | ***# Params*** | ***# Of obs*** | ***Test Statistic*** | ***dF*** | ***CFI*** | ***TLI*** | ***RMSEA*** | ***Lower CI*** | ***Upper CI*** | ***SRMR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 14 | *CFA EL* | 17 | 62 | 17.148 | 11 | 0.914 | 0.836 | 0.095 | 0 | 0.178 | 0.065 |
| 15 | *Baseline EL* | 12 | 62 | 29.076 | 16 | 0.817 | 0.76 | 0.115 | 0.042 | 0.18 | 0.149 |
| 16 | *Constrained EL* | 15 | 62 | 23.021 | 15 | 0.888 | 0.843 | 0.093 | 0 | 0.164 | 0.114 |
| **17** | ***Unconstrained EL*** | **15** | **62** | **14.815** | **13** | **0.975** | **0.959** | **0.047** | **0** | **0.139** | **0.057** |

*Best fit & CMV calculations are based on model highlighted in **bold**.

**Table 4.16: Model 8 measurements for Health & Safety super category**

| | ***α*** ***(Substantive Factor Loadings)*** | ***δ*** ***(Marker Factor Loadings)*** | ***θ*** ***(Marker Variances)*** |
|---|---|---|---|
| *HS1* | 0.707 | - | 5.999 |
| *MFC* | * | 0.428 | 0.5 |
| *MMC* | * | 0.71 | 0.496 |
| *MSC* | * | 0.587 | 0.656 |
| *MDO* | * | 0.655 | 0.571 |

**Table 4.17: Model 13 measurements for Labor super category**

| | ***β*** ***(Substantive Factor Loadings)*** | ***δ*** ***(Marker Factor Loadings)*** | ***θ*** ***(Marker Variances)*** |
|---|---|---|---|
| *CL* | 0.788 | -0.172 | 0.35 |
| *FL* | 0.697 | -0.009 | 0.514 |
| *FoA* | 0.352 | -0.406 | 0.711 |
| *HA* | 0.942 | 0.021 | 0.112 |
| *HW* | -0.009 | 0.904 | 0.183 |
| *ND* | 0.777 | -0.118 | 0.383 |
| *WB* | 0.022 | 0.923 | 0.147 |
| *WR* | 0.675 | 0.261 | 0.476 |
| *MFC* | * | 0.761 | 0.42 |
| *MMC* | * | 0.663 | 0.561 |
| *MSC* | * | 0.597 | 0.644 |
| *MDO* | * | 0.605 | 0.634 |

**Table 4.18: Model 17 measurements for Legal & Environmental super category**

| | ***γ*** ***(Substantive Factor Loadings)*** | ***δ*** ***(Marker Factor Loadings)*** | ***θ*** ***(Marker Variances)*** |
|---|---|---|---|
| *Env* | 0.021 | 0.504 | 0.746 |
| *IW* | 0.026 | 0.078 | 0.993 |
| *LC* | 6.911 | 0.223 | -46.812 |
| *MFC* | - | 0.085 | 0.352 |
| *MMC* | - | 0.64 | 0.59 |
| *MSC* | - | 0.598 | 0.642 |
| *MDO* | - | 0.593 | 0.648 |

## 4. 7 Analysis of Focal SCA Categories

Companies typically use one SCA to assess multiple categories of compliance. Through previous analysis it was demonstrated the CMV can be present in SCAs when the *O rates* are examined at super category level. However, through performing a similar analysis with Focal SCA category level we would not only be able to understand the effect of CMV on individual categories, but also potentially the group effects of super categories across the whole SCA. Taken as a whole, CMV present in individual Focal SCA categories could affect SCA outcomes differently.

Our approach to examine CMV effects on Focal SCA categories was similar to that of super categories. We began by examining the summary statistics of each individual category, followed by correlation analysis, Harman's test and finally a CFA marker variable method. The summary statistics and correlations were used to identify the relationship between various categories. In doing Harman's test, our goal was to detect whether CMV is present at this level of aggregation. The CFA marker variable method was then used to measure CMV within each focal SCA category, and the whole SCA. All analysis at SCA category level was conducted using DS2.

### 4.6.1 Summary Statistics

Table 4.7 showed the comparison between the number of violations reported by auditors and their corresponding O metrics. The Child Labor category had the lowest occurrence rate and 0.03, meaning auditors reported child labor occurrences in only 3% of all related audit questions. Health & Safety category had the largest number of questions in the audit protocol, and the largest number of violations reported, though it only had the third largest occurrence rate at 0.21. The category of Hours of Work had the highest occurrence rate, despite being only the third in total violations reported by auditors. Overall, the focal SCA categories of Child Labor and

Forced Labor (0.03 & 0.04) had the lowest occurrence rates, while the categories of Environment and Hours of work had the highest occurrence rates (0.24 & 0.33). The summary statistics for all focal SCA categories from DS2 is shown in table 4.18.

**Table 4.19 Summary Statistics for Focal SCA Categories**

| ***Focal SCA Category*** | *Mean* | *Std Dev* | *Range* | *Minimum* | *Maximum* | *N* |
|---|---|---|---|---|---|---|
| Child Labor | 0.0402 | 0.0701 | 0.3900 | 0.0000 | 0.3900 | 62.0000 |
| Environment | 0.1724 | 0.1537 | 0.7700 | 0.0000 | 0.7700 | 62.0000 |
| Forced Labor | 0.0377 | 0.0870 | 0.5200 | 0.0000 | 0.5200 | 62.0000 |
| Freedom of Association | 0.0706 | 0.0784 | 0.3300 | 0.0000 | 0.3300 | 62.0000 |
| Harassment & Abuse | 0.0863 | 0.1331 | 0.6300 | 0.0000 | 0.6300 | 62.0000 |
| Health & Safety | 0.2056 | 0.0762 | 0.3500 | 0.0400 | 0.3900 | 62.0000 |
| Hours of work | 0.2402 | 0.2176 | 0.6500 | 0.0000 | 0.6500 | 62.0000 |
| Informed Workplace | 0.0802 | 0.1213 | 0.6300 | 0.0000 | 0.6300 | 62.0000 |
| Legal Compliance | 0.1202 | 0.0894 | 0.5000 | 0.0000 | 0.5000 | 62.0000 |
| Non - Discrimination | 0.0716 | 0.1581 | 0.8000 | 0.0000 | 0.8000 | 62.0000 |
| Wages & Benefits | 0.0939 | 0.0807 | 0.3200 | 0.0000 | 0.3200 | 62.0000 |
| Women's rights | 0.1160 | 0.1495 | 0.6100 | 0.0000 | 0.6100 | 62.0000 |

**Table 4.20: Difference in means for focal SCA categories**

| ***Focal SCA Category*** | *Sample Mean* | *Audit Mean* | *Abs Difference* |
|---|---|---|---|
| Harassment & Abuse | 0.0863 | 0.0867 | 0.0004 |
| Forced Labor | 0.0377 | 0.037 | 0.0007 |
| Child Labor | 0.0402 | 0.0323 | 0.0079 |
| Health & Safety | 0.2056 | 0.214 | 0.0084 |
| Legal Compliance | 0.1202 | 0.133 | 0.0128 |
| Women's rights | 0.116 | 0.1299 | 0.0139 |
| Informed Workplace | 0.0802 | 0.0615 | 0.0187 |
| Freedom of Association | 0.0706 | 0.0492 | 0.0214 |
| Wages & Benefits | 0.0939 | 0.1206 | 0.0267 |
| Non - Discrimination | 0.0716 | 0.0427 | 0.0289 |
| Environment | 0.1724 | 0.2426 | 0.0702 |
| Hours of work | 0.2402 | 0.333 | 0.0928 |

We review the summary statistics of some noteworthy categories below:

*Child Labor*: The Child Labor category had the lowest mean occurrence rate measured reported by auditors in DS2. The mean occurrence reported was 0.04, and the occurrence rate ranged between 0 to 0.39. Only one auditor had reported a high occurrence rate above 0.3 and the distribution of this category hence exhibited a skew towards lower occurrence rate. We hence consider the higher value to be an outlier. However, the DS2 sample observations were higher than the overall occurrence rate measured indicating there could be bias in measurement of child labor by auditors.

*Environment*: The O rates for Environment category were found to be normally distributed with a mean of 0.1724. 61% of auditors had occurrence rates lower than 0.2, and the distribution was skewed towards lower values. This category also had the second largest range of values and third largest standard deviation among all Focal SCA categories. There was also a major difference between the dataset mean and the audit mean, indicating potentially large bias in measurement.

*Forced Labor*: The Forced Labor category had the second lowest bias in measurement. The O-rates for this category ranged from 0 to 0.52. 92% of auditors had reported occurrence rates in the lower quartile of the distribution, indicating that this may not be a very frequently observed issue.

*Harassment & Abuse*: The bias measure for Harassment & Abuse category was the lowest at 0.0004 for difference in means. The distribution for this category was also skewed more towards the lower quartile, with 90% of auditors in that range. The mean occurrence rate observed by auditors was 0.09, with a standard deviation of 0.1331. Auditors had reported 591 violations in this category.

*Health & Safety*: The focal category of Health & Safety had the greatest number of audit questions, as well as the most numerous violations reported by auditors. This category was also unique in that it was the only Focal SCA category that was also a super category. The total number of violations reported for this category was 65,566, which was an outlier among other categories. However, the O rate for this category was 0.21. Having the largest number of violations, this category O rates were normally distributed, with 46% of auditors reporting violation rates below mean, spread over a range of 0.35. Health & Safety category had a bias measure of 0.0084.

*Hours of Work*: With 7090 reported violations and a O rate of 0.33, Hours of Work category had the greatest occurrence rate among all Focal SCA categories. This category also had a skewed distribution with three models. The largest mode was 0.05, while other modes were at 0.3 and 0.6, respectively. 42% of auditors were distributed around the lowest mode, and the mean occurrence rate for the auditor sample was 0.24. This category also had the largest measured bias among all focal SCA categories.

*Wages & Benefits*: This SCA category had 11694 reported violations, with an occurrence rate of 0.1206. The sample mean 0.0939 was different from the audit mean, yielding a bias of 0.0267. The overall distribution was once again skewed towards lower occurrence rate, with 61% of auditors reporting occurrence rates below 0.1.

The occurrence rates and distribution of other focal SCA categories, namely Non – Discrimination, Informed Workplace, Freedom of Association, Women's Rights and Legal Compliance are provided in tables 18 and 18A. The distribution plots for SCA categories are shown in Appendix (iii).

The analysis of summary statistics of Focal SCA categories revealed that Non – Discrimination, Environment & Hours of Work categories were subject to the greatest bias. While the categories of Harassment & Abuse, Forced Labor and Child Labor exhibited the smallest bias measures. In all cases except Health & Safety and Hours of Work, the distribution of occurrence rates exhibited a skew towards lower values indicating these categories may be subject to leniency bias.

### 4.6.2 SCA Category Correlations

Knowing the bias effects in various categories, we proceed to understanding the influence of CMV on O rates. Since high correlations could indicate higher influence or presence of CMV between the SCA categories, we computed the Pearson's correlation coefficients between them. This information is shown in table 4.19 below.

**Table 4.21: Focal SCA category correlations**

| ***Correlations*** | ***CL*** | ***Env*** | ***FL*** | ***FoA*** | ***HB*** | ***HS*** | ***HW*** | ***IW*** | ***LC*** | ***ND*** | ***WB*** | ***WR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***CL*** | 1 | | | | | | | | | | | |
| ***Env*** | -0.1086 | 1 | | | | | | | | | | |
| ***FL*** | 0.5783 | 0.0927 | 1 | | | | | | | | | |
| ***FoA*** | 0.3586 | -0.2297 | 0.1021 | 1 | | | | | | | | |
| ***HB*** | 0.7501 | 0.153 | 0.6478 | 0.3349 | 1 | | | | | | | |
| ***HS*** | 0.3942 | 0.3874 | 0.438 | 0.228 | 0.5431 | 1 | | | | | | |
| ***HW*** | -0.1225 | 0.5553 | 0.0032 | -0.4245 | 0.0143 | 0.2855 | 1 | | | | | |
| ***IW*** | 0.4744 | -0.0094 | 0.3211 | 0.4472 | 0.6753 | 0.4236 | -0.0547 | 1 | | | | |
| ***LC*** | 0.1686 | 0.2515 | 0.156 | -0.0162 | 0.2727 | 0.4205 | 0.2108 | 0.1871 | 1 | | | |
| ***ND*** | 0.6032 | -0.1434 | 0.4768 | 0.393 | 0.7344 | 0.3819 | -0.1361 | 0.5807 | 0.2253 | 1 | | |
| ***WB*** | -0.1447 | 0.4568 | -0.044 | -0.3813 | 0.029 | 0.3213 | 0.8352 | 0.0075 | 0.3528 | -0.0365 | 1 | |
| ***WR*** | 0.4304 | 0.1362 | 0.6295 | 0.0789 | 0.6217 | 0.5814 | 0.1788 | 0.4266 | 0.3151 | 0.5399 | 0.3006 | 1 |

A total of 66 correlation values were computed, of which 53 category pairs showed positive correlations and 13 category pairs showed negative correlations. The top 5 negative correlation pairs were observed between Freedom of Association/Hours of Work, Freedom of Association / Wages & Benefits, Freedom of Association / Environment, Wages & Benefits / Child Labor, Environment / Non-discrimination category pairs. This suggests that auditors who reported high/low O rates for the former categories, reported the dissimilar occurrences for the latter categories. For example, auditors who reported Low Occurrence rates in Freedom of Association category, reported high occurrences in Hours of Work, Wages & Benefits and Environment categories.

It should be noted here that 64% of auditors formed the lowest quartile of occurrence rates for the Freedom of Association category. The distribution of Hours of Work and Wages Benefits also exhibited multiple modes. The distribution of Environment category, while skewed towards lower values, also exhibited a wide range. All these factors indicate that O rates in these categories could the CMV effects.

A majority of SCA categories however exhibited positive correlations. A total of 34 correlation pairs exhibited very high coefficients (above 0.3). 16 correlation pairs were found to be greater than 0.5. The highest correlation coefficient was between Hours of work and Wages & Benefits. The distributions of these two categories share a lot of similarities, though the range of Hours of Work occurrence rate is greater than Wages & Benefits. The category of Hours of Work also had the greatest bias measurement as seen in the earlier section.

The occurrence rate of Harassment & Abuse also showed remarkably high correlations with Child Labor, non – Discrimination, Informed Workplace & Forced Labor. Similarly, Women's Rights category also exhibited high correlation with the occurrence rates of

Forced Labor, Health & Safety and Non – Discrimination. These relationships indicate that, auditors tend to follow similar patterns in reporting violations in these categories. The other relationships between these categories we discuss in the later sections.

### 4.6.3 Harman's test for SCA Categories

The results from Harman's test for SCA categories is shown in table 4.20. Harman's test failed to detect presence of CMV at SCA category level. While the analysis of summary statistics and correlations indicated that CMV could influence the *O rates* are SCA category level, the results from Harman's test indicate that their overall outcome across all categories could be moderated due to individual category effects. Harman's test yielded one factor that only accounted 37.848% of all SCA category factor loadings.

**Table 4.22: Harman's test results for SCA categories**

| *Unrotated Factor Loading* | | | *Variance Explained by Each Factor* | | | |
|---|---|---|---|---|---|---|
| ***SCA Category*** | ***Factor 1*** | | ***Factor*** | ***Variance*** | ***Percent*** | ***Cum Percent*** |
| HB | 0.9149601 | | Factor 1 | 4.5418 | 37.848 | 37.848 |
| ND | 0.7897824 | | | | | |
| WR | 0.7692756 | | | | | |
| CL | 0.7635899 | | | | | |
| FL | 0.7202389 | | | | | |
| IW | 0.7200676 | | | | | |
| HS | 0.7159851 | | | | | |
| LC | 0.403682 | | | | | |
| FoA | 0.3955742 | | | | | |
| Env | 0.1368341 | | | | | |
| WB | 0.1202728 | | | | | |
| HW | 0.0594472 | | | | | |

Traditionally, Harman's One-Factor Test indicates problematic CMV if an exploratory factor analysis (EFA) with all study variables produces eigenvalues suggesting the first factor accounts for more than 50% of the variance among variables (Fuller et al, 2016). Among the

shortcomings stated for Harman's test includes conditions where CMV is present in the data, but the tests fail to detect bias. Hence, this has recently led authors to believe that Harman's test may not be sensitive enough to detect CMV, though there is no empirical evidence to support this. (Fuller et al 2016; Podsakoff & Mackenzie, 2003).

### 4.6.3 CFA Marker Variable Analysis for SCA categories

According to Fuller et al (2016), despite CMV measurement using the CFA marker technique being one of the least adopted, it is more precise, accurate & sensitive than Harman's test in detecting and measuring CMV.

Our CFA model to measure CMV at SCA categories level is different from that in super category level. To measure CMV at SCA category level, we implement a four factor CFA model where all SCA categories are loaded on to their respective super categories simultaneously. The marker variables are then loaded on to a separate factor, which we call the method factor. For the priming model, all factors are allowed to correlate with each other. In other models, the method factor is not allowed to correlate with the substantive factors. Four models are run to determine the best fit. It was found that the unconstrained model had the best fit indices. Following this, CMV was calculated using Williams – Hartman – Cavazotte formula. The construction of the 4 factor CFA model allows us to estimate the CMV for all categories of a SCA, including super categories

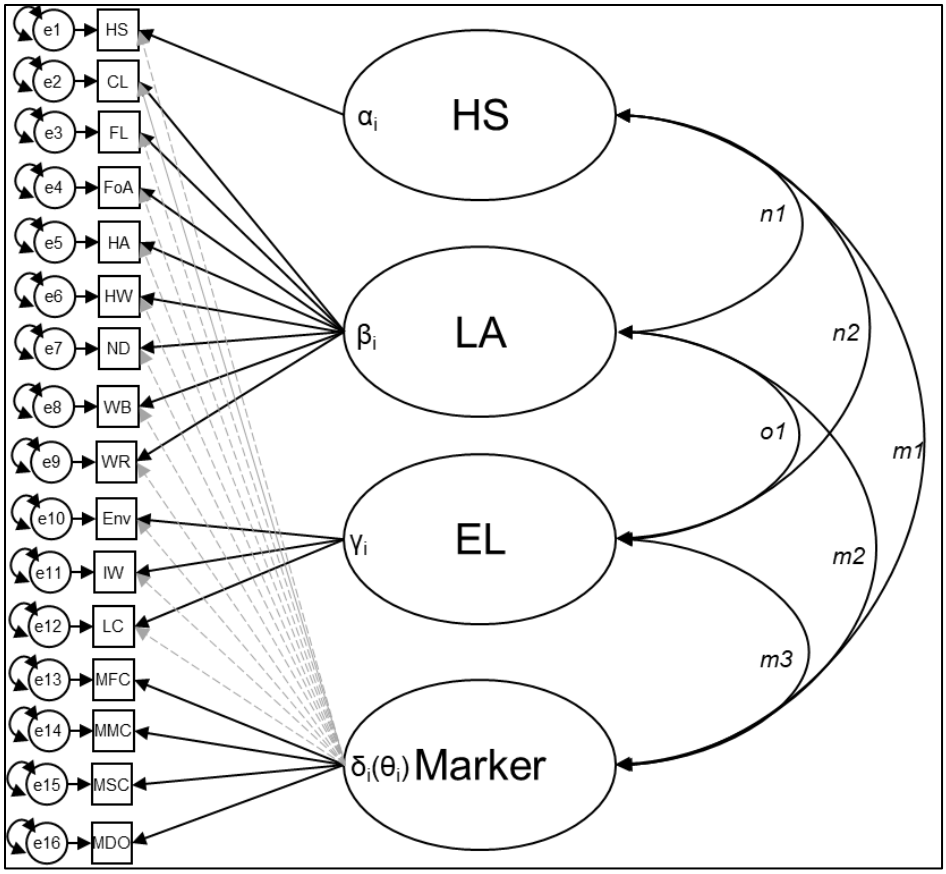


**Figure 4.11: Priming model for SCA category level analysis**

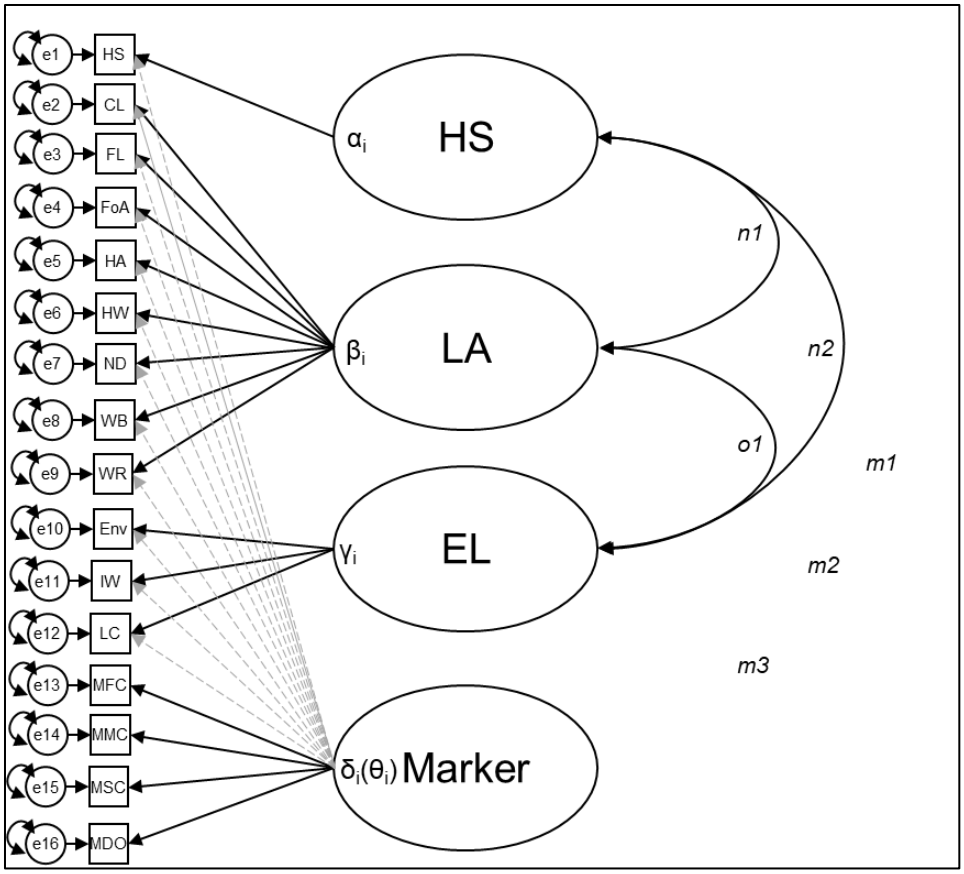


**Figure 4.12: Measurement model for SCA category level analysis**

The 4 models which were run were designated model 0,1,2,3 using DS2. *Model 0* is the priming model used to evaluate factor loading with the method factors allowed to correlate with the substantive factors. The method factor loadings were measured using variable $\delta_i$ and their variance using variable $\theta_i$. The corresponding substantive factor loadings are measured as $\alpha_i$ for Health & Safety, $\beta_i$ for Labor and $\gamma_i$ for Legal & Environmental. Where *i* is the corresponding Focal SCA category. Of the 4 models run, the unconstrained model *(model 3)* exhibited the best fit indices, indicating that CMV is present within SCA categories, and it has unequal effects on factors.

**Table 4.23: CFA model fit measurements for SCA categories**

| ***Model #*** | ***Name*** | ***# Params*** | ***# Of obs*** | ***Test Statistic*** | ***dF*** | ***CFI*** | ***TLI*** | ***RMSEA*** | ***Lower CI*** | ***Upper CI*** | ***SRMR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Priming ALL | 42 | 62 | 347.708 | 94 | 0.536 | 0.407 | 0.209 | 0.185 | 0.232 | 0.222 |
| 1 | Baseline ALL | 35 | 62 | 363.819 | 101 | 0.519 | 0.429 | 0.205 | 0.182 | 0.228 | 0.23 |
| 2 | Constrained ALL | 47 | 62 | 300.574 | 100 | 0.633 | 0.56 | 0.18 | 0.157 | 0.203 | 0.46 |
| **3** | **Unconstrained ALL** | **47** | **62** | **156.23** | **89** | **0.877** | **0.834** | **0.11** | **0.081** | **0.139** | **0.075** |

*Best fit & CMV calculations are based on model highlighted in **bold**.

The CFA model results showed that common method variance accounted for 11.4% of the overall reliability of SCAs. The SCA categories of Hours of Work and Wages & Benefits were the most affected, where CMV values were measured at 100%. This was followed by Environment category, where CMV accounted for 95% of reliability. The categories of Forced Labor, Harassment & Abuse, and Informed Workplace did not show any effects of CMV. In other categories, CMV effects on reliability varied from 3% for Non-discrimination to 55% for Legal Compliance. The table of CMV measured for all super categories and Focal SCA categories is shown below in table 4.22 and 4.23.

**Table 4.24: Model 3 measurements for Focal SCA Categories**

| *Super Categories* | *Category Variables* | *Substantive Factor Loadings* | *δ (Marker Factor Loadings)* | *θ (Marker Variances)* |
|---|---|---|---|---|
| **Health & Safety (α)** | HS | 1.919 | 0.357 | -2.811 |
| **Labor (β)** | CL | 0.777 | -0.177 | 0.365 |
| | FL | 0.682 | -0.004 | 0.535 |
| | FoA | 0.375 | -0.405 | 0.695 |
| | HA | 0.95 | 0.021 | 0.096 |
| | HW | -0.012 | 0.909 | 0.1173 |
| | ND | 0.776 | -0.132 | 0.381 |
| | WB | 0.023 | 0.916 | 0.161 |
| | WR | 0.674 | 0.258 | 0.479 |
| **Legal & Environmental (γ)** | Env | 0.123 | 0.555 | 0.676 |
| | IW | 0.588 | -0.015 | 0.654 |
| | LC | 0.274 | 0.301 | 0.835 |
| | MFC | - | 0.766 | 0.413 |
| | MMC | - | 0.649 | 0.579 |
| | MSC | - | 0.575 | 0.669 |
| | MDO | - | 0.631 | 0.601 |

**Table 4.25: CMV calculation for Focal SCA Categories**

| | *Category Variables* | $R_t$ | $R_m$ | $C_i$ *(CMV)* |
|---|---|---|---|---|
| *Super Categories* | HS | 3.814 | 0.128 | 3.3% |
| | LA | 0.876 | 0.084 | 9.6% |
| | LE | 0.437 | 0.184 | 42.2% |
| *Focal SCA Categories* | HS | 3.814 | 0.128 | 3.3% |
| | CL | 0.635 | 0.031 | 4.9% |
| | FL | 0.465 | 0.000 | 0.0% |
| | FoA | 0.305 | 0.164 | 53.8% |
| | HA | 0.904 | 0.000 | 0.0% |
| | HW | 0.876 | 0.876 | 100.0% |
| | ND | 0.619 | 0.017 | 2.8% |
| | WB | 0.839 | 0.839 | 99.9% |
| | WR | 0.521 | 0.067 | 12.8% |
| | Env | 0.323 | 0.308 | 95.3% |
| | IW | 0.346 | 0.000 | 0.1% |
| | LC | 0.166 | 0.091 | 54.7% |
| ***Total SCA*** | | **0.964** | **0.111** | **11.6%** |

## 4. 8 CMV Comparison Between Countries

Many global companies often utilize a centralized code of conduct as a framework to build their SCAs. This often means that questions within SCAs may not be applicable equally to all countries due to changes in laws and regulations. For larger countries, there could also be the possibility of differences in labor laws within the country. Often time auditors themselves travel between various countries to perform SCAs. Hence to compare the occurrence of CMV between

audits happening in two countries, we utilized DS2 & DS4. Both these datasets had a similar structure and variables as DS2, but only contained auditors who had performed audits in the respective countries of comparison. From SDS, it was identified that only China & USA had sufficient number of auditors for performing this analysis in order to keep normal distribution assumptions and to ensure sufficient sample sizes. All other countries had less than 15 auditors per country. In case of China there were 21 unique auditors, and there were 16 auditors unique to USA. CMV measurement for country specific analysis was done using CFA marker variable method.

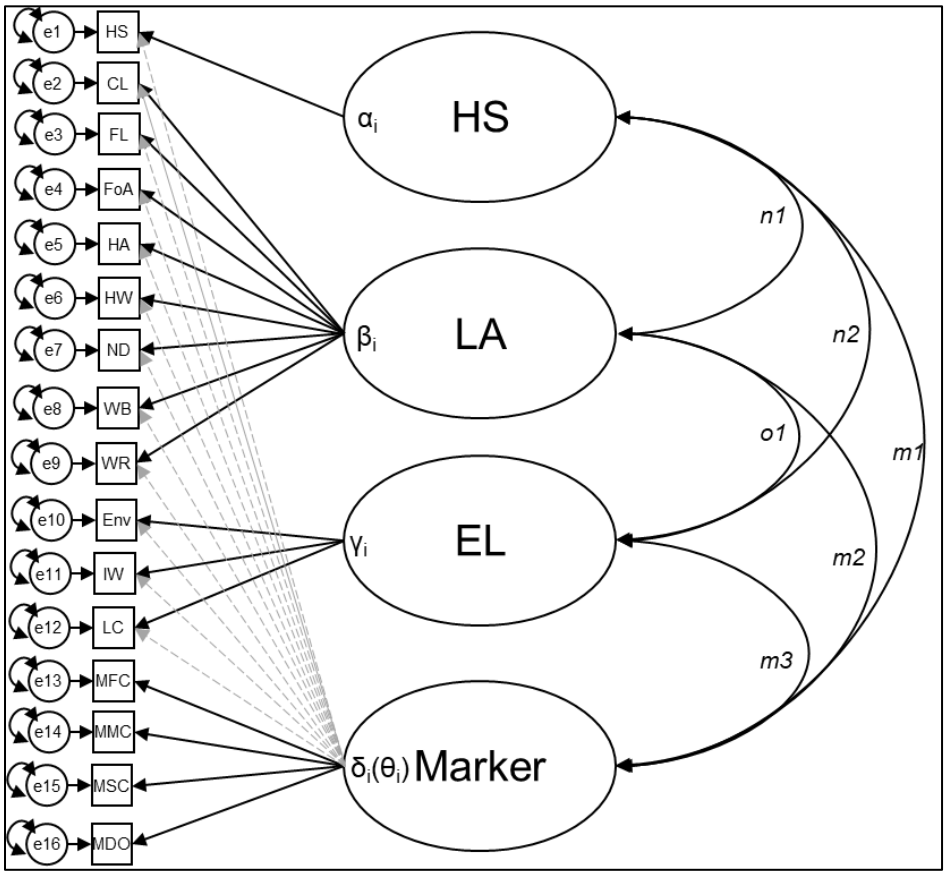


**Figure 4.13: Priming model for Country comparison (China & USA)**

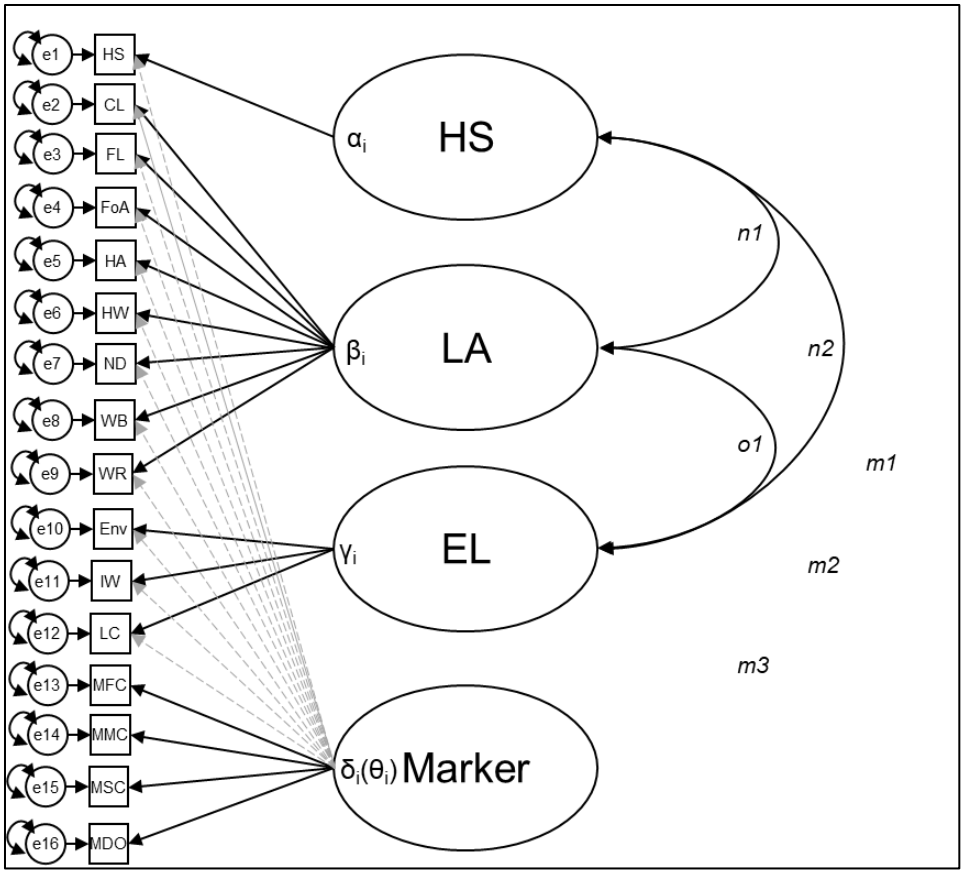


**Figure 4.14: Measurement model for Country comparison (China & USA)**

For comparing CMV occurrence between countries, 8 models were run using DS3 and DS4 to understand the effects of CMV on auditor reported occurrence rates. Both these datasets were obtained by sub-sampling SDS to include audits conducted only in the respective countries. In both the cases, it the unconstrained model had the best fit measures indicating the CMV effects were not uniform among SCA categories in both countries. *Model 21* and *model 25* were used to calculate CMVs for China and USA respectively.

**Table 4.26: CFA model fit measurements for China (DS3)**

| ***Model #*** | ***Name*** | ***# Params*** | ***# Of obs*** | ***Test Statistic*** | ***dF*** | ***CFI*** | ***TLI*** | ***RMSEA*** | ***Lower CI*** | ***Upper CI*** | ***SRMR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 18 | CFA China | 42 | 26 | 322.577 | 94 | 0.385 | 0.215 | 0.306 | 0.27 | 0.343 | 0.221 |
| 19 | Baseline China | 35 | 26 | 348.056 | 101 | 0.335 | 0.21 | 0.307 | 0.272 | 0.342 | 0.262 |
| 20 | Constrained China | 47 | 26 | 297.017 | 100 | 0.47 | 0.364 | 0.275 | 0.239 | 0.312 | 0.309 |
| **21** | **Unconstrained China** | **47** | **26** | **258.25** | **89** | **0.544** | **0.386** | **0.27** | **0.232** | **0.309** | **0.158** |

**Table 4.27: CFA model fit measurements for USA (DS4)**

| ***Model #*** | ***Name*** | ***# Params*** | ***# Of obs*** | ***Test Statistic*** | ***dF*** | ***CFI*** | ***TLI*** | ***RMSEA*** | ***Lower CI*** | ***Upper CI*** | ***SRMR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | CFA US | 40 | 17 | 168.618 | 80 | 0.339 | 0.132 | 0.255 | 0.201 | 0.309 | 0.223 |
| 23 | Baseline US | 34 | 17 | 175.645 | 86 | 0.331 | 0.184 | 0.248 | 0.195 | 0.3 | 0.236 |
| 24 | Constrained US | 46 | 17 | 172.773 | 85 | 0.345 | 0.191 | 0.246 | 0.193 | 0.299 | 0.236 |
| **25** | **Unconstrained US** | **46** | **17** | **239.07** | **105** | **0.458** | **0.231** | **0.24** | **0.183** | **0.297** | **0.289** |

*Best fit & CMV calculations are based on model highlighted in **bold**.

**Table 4.28: Model 21 measurements for Focal SCA Categories (China)**

| *Super Categories* | *Category Variables* | *Substantive Factor Loadings* | *δ (Marker Factor Loadings)* | *θ (Marker Variances)* |
|---|---|---|---|---|
| **Health & Safety (α)** | HS | 0.47 | 0.01 | -0.046 |
| **Labor (β)** | CL | 0.167 | 0.019 | 0.001 |
| | FL | 0.086 | 0.021 | 0.002 |
| | FoA | 0.19 | 0.014 | 0.002 |
| | HA | 0.129 | 0.03 | 0.001 |
| | HW | -0.043 | 0.181 | 0.008 |
| | ND | 0.138 | 0.024 | 0.001 |
| | WB | -0.08 | 0.08 | 0 |
| | WR | -0.053 | 0.091 | 0.01 |
| **Legal & Environmental (γ)** | Env | 0.904 | 0.054 | 0.008 |
| | IW | 0.252 | 0.006 | 0.022 |
| | LC | 0.244 | 0.016 | 0.002 |

**Table 4.29: Model 21 measurements for Focal SCA Categories (USA)**

| *Super Categories* | *Category Variables* | *Substantive Factor Loadings* | *δ (Marker Factor Loadings)* | *θ (Marker Variances)* |
|---|---|---|---|---|
| **Health & Safety (α)** | HS | 0.022 | -0.011 | 0.008 |
| **Labor (β)** | CL | -0.005 | 1.707 | -0.096 |
| | FL | 0 | 0.01 | 0.001 |
| | FoA | -0.001 | -0.044 | 0.008 |
| | HA | 0.002 | 0.017 | 0.001 |
| | HW | -0.001 | -0.021 | 0.014 |
| | ND | 0.011 | 0.005 | 0.014 |
| | WB | 0 | 0.008 | 0.001 |
| | WR | 4.431 | 0.107 | -3.319 |

**Table 4.29 (continued) : Model 21 measurements for Focal SCA Categories (USA)**

| *Super Categories* | *Category Variables* | *Substantive Factor Loadings* | *δ (Marker Factor Loadings)* | *θ (Marker Variances)* |
|---|---|---|---|---|
| **Legal & Environmental (γ)** | Env | 1.195 | -0.008 | -1.177 |
| | IW | 0.005 | -0.003 | 0.014 |
| | LC | 0 | -0.038 | 0.019 |

**Table 4.30: CMV calculation for Focal SCA Categories (China)**

| *Category Variables* | $R_t$ | $R_m$ | $C_i$ *(CMV)* |
|---|---|---|---|
| HS | 1.263 | 0.001 | 0.0% |
| CL | 0.966 | 0.012 | 1.3% |
| FL | 0.797 | 0.045 | 5.6% |
| FoA | 0.948 | 0.005 | 0.5% |
| HA | 0.946 | 0.049 | 5.1% |
| HW | 0.812 | 0.769 | 94.7% |
| ND | 0.952 | 0.028 | 2.9% |
| WB | 1.000 | 0.500 | 50.0% |
| WR | 0.526 | 0.393 | 74.7% |
| Env | 0.990 | 0.004 | 0.4% |
| IW | 0.743 | 0.000 | 0.1% |
| LC | 0.968 | 0.004 | 0.4% |
| ***Total SCA (China)*** | 0.998 | 0.049 | 4.9% |

**Table 4.31: CMV calculation for Focal SCA Categories (USA)**

| *Category Variables* | $R_t$ | $R_m$ | $C_i$ *(CMV)* |
|---|---|---|---|
| HS | 0.070 | 0.014 | 20.0% |
| CL | 1.034 | 1.034 | 100.0% |
| FL | 0.500 | 0.050 | 10.0% |
| FoA | 0.813 | 0.045 | 5.6% |
| HA | 0.464 | 0.155 | 33.4% |
| HW | 0.328 | 0.021 | 6.4% |
| ND | 0.372 | 0.001 | 0.3% |
| WB | 0.749 | 0.016 | 2.1% |
| WR | -0.003 | -0.003 | 99.7% |
| Env | 0.000 | 0.000 | 20.0% |
| IW | 0.001 | 0.001 | 100.0% |
| LC | 0.071 | 0.071 | 100.0% |
| ***Total SCA (China)*** | 1.148 | 0.098 | 8.5% |

Overall, the reliability measure of CMV in the violation occurrence rates of China was 4.9%. The effect was spread wide, with categories like Hours of Work and Women's rights having their CMV effects at 94.7% and 74.7% respectively. While the categories of Health & Safety, Informed Workplace, Environment, Legal compliance, and Freedom of Association being affected by less than 1%.

On the other hand, CMV affects the reliability of violation occurrence rates in the USA by 8.5%. The largest effects are seen in the categories of Child Labor, Informed Workplace & Legal Compliance, where the model predicted CMV occurrence with 100% reliability. The category of Non – Discrimination however is least affected by CMV at only 0.3%. It is noteworthy to mention that O rates for all SCA categories may exhibit CMV within USA data.

The results from the country comparison show that CMV occurrence can vary between auditing groups across countries. For instance, within the auditing sample considered in this study, CMV occurrence (as a measure of reliability) for audits undertaken in all countries was 9.5%, for China it was 4.9% and for USA it was 8.5%. The effect of CMV across SCA categories was not uniform, which can be confirmed from the CMV measurements. Some SCA categories are more susceptible to CMV than others. It is important to note that there could be sources of bias other than CMV which could affect the occurrence rates reported by auditors. The reasons for this variance are discussed in Chapter 5.

### 4. 9 Latent Variable measurements

SCA violations reported in this study were grouped into three super categories based on review of COC of the corporation associated with the audits. These super categories were further used as latent constructs to operationalize the CFA marker technique. While this structure conformed to the native categorization of the SCA studied, it could not provide sufficient information about actual latent constructs measured using them. An exploratory factor analysis was hence conducted on DS2 to understand the order to latent factors present within SCA categories. According to O'Leary-Kelly & Vokurka (1998), Exploratory Factor Analysis (EFA) is one of the frequently used methods by researchers to examine construct validity and latent factor measurements. In our case, the EFA analysis was used to rule out the presence of one-dimensionality, and explore the latent constructs measured by the Occurrence rate variable. The metric would be considered valid if more than one factor emerged from the EFA model.

**Table 4.32: EFA model factors**

| | Variance | % | Cum % |
|---|---|---|---|
| **Factor 1** | 4.0916 | 34.096 | |
| **Factor 2** | 2.525 | 21.042 | 55.138 |

**Table 4.33: EFA model Factor Loadings**

| | Factor 1 | Factor 2 |
|---|---|---|
| HA | 0.944232 | |
| ND | 0.780922 | |
| CL | 0.780416 | |
| IW | 0.694079 | |
| FL | 0.680169 | |
| WR | 0.667772 | |
| HS | 0.583153 | 0.364832 |
| FoA | 0.399245 | -0.42708 |
| WB | | 0.911313 |
| HW | | 0.908625 |
| Env | | 0.57496 |
| LC | | 0.331937 |

We used common factor analysis approach to assess the communality of the factors estimated by the EFA model. The factoring method employed was based on maximum likelihood. The results of the model suggested the presence of two latent factors. A significance test indicated that the 2 factors were sufficient for fit. The model had a Tucker Lewis index of

0.876 and an RMSEA of 0.118. Values above 0.3 were considered significant for factor loadings. Both the factors provided by the model cumulatively accounted for 55% of the variance in model estimates.

In the above two factors, Factor 1 (34.096% of variance) was the larger one. The significant variables encapsulated by this factor are Harassment & Abuse, non – Discrimination, Child Labor, Informed Workplace, Forced Labor, Women's Rights, Health & Safety, Freedom of Association. Factor 2, which was the smaller one accounted for 21.042% of the variance. Health & Safety, Freedom of Association, Wages & Benefits, Hours of Work, Environment & Legal Compliance were the SCA categories captured within this factor. The SCA categories of Health & Safety and Freedom of Association were associated with both the factors. We observe that the significant variables in Factor 1 constitute measure of Worker Treatment, while that in Factor 2 indicate Objective compliance with local laws related to labor, environment, and other regulatory permits.

### 4. 10 Method Descriptions

Though occurrence rates reported by auditors are bounded measures, the primary method of assessing factor compliance remains examination of qualitative information association with a violation. To understand the influence commonality in methods may have on the occurrence rates, we also qualitatively examined the methods utilized by auditors to audit SCA categories that showed extreme correlations. The involved examining the steps undertaken by auditors while evaluating a SCA category and the type of evidence used to substantiate the occurrence of a violation. It was observed the for the SCA categories that shared high correlations, there was high commonality in methods, while for categories that showed negative correlations, there was large discrepancy in methods.

Specifically, the categories of Child Labor, non – Discrimination, Harassment & Abuse, Women's rights had the highest positive correlations with other SCA categories. The primary method of reporting violations in this category involved examination of factory policies and documentation by an auditor. On the other hand, the SCA categories of Wages & Benefits, Freedom of Association & Environment had the lowest negative correlations with other SCA categories. Typical methods for auditing these categories involved examination of physical evidence such as collecting wastewater samples, reviewing pay slips etc. For example, an auditor who reported high child labor violation rates also reported high rates for Forced Labor, Harassment & Abuse and non – Discrimination, and low violation rates in Environment, Hours of Work and Wages & Benefits. The method descriptions for SCA categories examines are shown in tables 4.32 and 4.33 below.

**Table 4.34: Method Descriptions for SCA categories showing high positive correlations**

| **Child Labor** |
|---|
| Number of questions: 2<br><br>Steps:<br>1. Review factory policies<br>2. Interview associates of "young" appearance (judgement-based sampling)<br>3. Verify associate age documentation<br>4. Legal restriction and employment guidelines for juvenile associates<br>5. Obtain list of juvenile employees<br><br>Evidence: Photos, documentation, notes |

**Table 4.34 (continued): Method Descriptions for SCA categories showing high positive correlations**

| **Non – Discrimination** |
|---|
| Number of questions: 1<br><br>Steps:<br>1. Review factory nondiscrimination policy for detail support of Principle 8.<br>2. Review documented factory grievances relating to discrimination.<br>3. Interview associates to assess situations where discrimination might take place.<br>4. Review of nondiscrimination communicated to third parties who may recruit and screen applicants on the facility's behalf<br><br>Evidence: Documentation, grievance system |
| **Harassment & Abuse** |
| Number of questions: 1<br><br>Steps:<br>1. Review harassment policy<br>2. Review factory training for management, supervision, associates, and third-party service providers relating to harassment.<br>3. Review factory grievances relating to any potential instances of harassment.<br>4. Interview associates to assess situations where harassment might take place.<br>5. Review the factory's system for assessing disciplinary fines.<br><br>Evidence: Training materials, documentation, grievance system, payroll deductions |

**Table 4.34 (continued): Method Descriptions for SCA categories showing high positive correlations**

| Women's rights |
|---|
| Number of questions: 1<br><br>Steps:<br>1. Review the following for women:<br>a. Remuneration<br>b. Pregnancy tests<br>c. Maternity benefits<br>d. Contraception<br>e. Reproductive health conditions<br>f. Childcare<br>g. Lactation facilities<br><br>Evidence: Documentation |

**Table 4.35: Method Descriptions for SCA categories showing high negative correlations**

| Wages & Benefits |
|---|
| Number of questions: 9<br><br>Steps:<br>1) Factory provides fair compensation, at least legal minimum wage<br>2) Factory provides legally mandated benefits & services<br>3) Determine facility compensates for overtime in accordance with law<br>4) Determine factory provides clear pay slips<br>5) Determine if factory uses home employment<br>6) Determine frequency of payroll<br>7) Retention of payroll records<br>8) Provision for rest & meal breaks<br>9) Determine if temporary/seasonal workers are compensated in legal & timely manner<br><br>Evidence: Documentation, Photos |

**Table 4.35 (continued): Method Descriptions for SCA categories showing high negative correlations**

| **Environment** |
|---|
| Number of questions: 1<br><br>Steps:<br>1) Status of environment discharge permits<br>2) Inspect chemical storage<br>3) Inspect process for managing solid waste<br><br>Evidence: Photos, documentation |
| **Freedom of Association** |
| Number of questions: 1<br><br>Steps:<br>4) Determine if factory guidelines are current<br>5) Confirm FoA materials are shared<br>6) Confirm union participation<br><br>Evidence: Documentation |

# CHAPTER 5

## Summary and Discussion

This study began by studying the existing literature on auditing, bias and SCAs. Through this exercise a gap in knowledge was identified, which was framed as the research questions for this dissertation. To examine the research questions, we collected data using existing SCAs that were analyzed for auditor bias. In this chapter, the results of the study are interpreted. Further, the implications, findings, future opportunities, and limitations of the study are presented. The results of this research are applicable to supply chain risk management, particularly within the apparel industry. The empirical investigation undertaken in this research focuses on analyzing the various structural components of SCAs, aggregated at various levels in the context of one COC.

### 5.1 Research Overview

Audits overall have gained increased prominence in the recent decades. For instance, even back in 2002, Bartley (2002) observed that the total number of audits conducted in early 2000s have increased three-fold compared to 1990s. Over the past couple decades, with the increased adoption of corporate COCs, Supplier Compliance Audits (SCAs) have become go to tools to assess and enforce compliance in supply chain. Many aspects of SCAs are subject to human judgment, that often rely on skill and subjective interpretation of a setting to report a non-conformity. Hence, the understanding the areas of audits that are subject to biases, provides an opportunity to improve the entire process of auditing by providing provide better insight into findings and remediation.

We began this research by studying existing literature on SCAs, with a goal to understand their role in the apparel industry. Next, theories and frameworks related to measuring audit outcomes were examined. Finally, literature related to measuring audit impact on business decisions was examined, specifically with a focus on auditor bias.

Recently, the fashion and apparel industry has resorted to increased use of SCAs to address ongoing criticism about industry practices. Various auditing tools and frameworks such as the SLCP (Social and Labor Convergence Program) have been recently designed to provide standardization of SCAs within the apparel industry. (SLCP website, 2022) However, the efficacy of audits as tools for remediation and improvement continue to remain in question. While many articles we examined were critical of audits and their purported benefits, the usage of audits to assess supplier compliance has only increased. Studies in the past have utilized many approaches to examine overall audit outcomes. However, only two studies we examined discussed the structural components of SCAs, such as a category of issues (Caro et al, 2021; Distelhorst et al, 2016).

In trying to understand audit outcomes, multiple authors point out the several factors that influence them. Some noteworthy factors include: Auditor Leniency (Kraft et al, 2022); prior experience of an auditor (Ball et al, 2016); auditor traits, composition of auditing teams (Short et al, 2016); auditor aggressiveness (Nelson & Tan, 2005); Disparate laws and regulations across countries and states (Havinga & Verbuggen, 2017); Technology (Ramamoorthi, 2003) and Buyer – Supplier relationships (Liu et al, 2019). Some studies also pointed to analyzing audit outcomes over a period of time (Locke, 2007; Distelhorst et al, 2016). It was inferred that wide variety of analysis have been adopted to examine audit outcomes.

Knowing the factors that affect auditing outcomes, we expected that audit outcomes would be biased. Recognition of the sources of common method bias such as social desirability, acquiescence, leniency & mood (Podsakoff et al, 2003; Gorrell et al, 2011), we postulated that systematic understanding of auditor bias could inform audit design and implementation by addressing the study's research objectives:

**RO1:** Is auditor bias present in Supplier Compliance Audits?

**RO2:** Does the occurrence of auditor bias differ among various SCA categories? (Labor, Legal & Environmental, Health & Safety)

**RO3:** Does auditor bias vary between countries?

A standard definition for auditor bias was first introduced in order to enable its measurement. Use the description of CMB, we defined auditor bias as "*the systematic error variance shared among audit categories measured using the same audit protocol by different auditors.*" Next, the research measured CMB in SCAs, using the actual audit data. We constructed the metric *violence occurrence rate* using an analytical model that mimicked the audit protocol structure of corporation. In the analytical model, each audit question was grouped into SCA categories, which were further aligned to three super categories classified as Health & Safety, Labor and Legal & Environmental as shown in Table 3.1.

The analytical model yielded four datasets which were examined to assess the research objectives. First, the presence of auditor bias was assessed at the super category and SCA category level. This was followed by measurement of auditor bias at super category and SCA category level. After which, the amount of auditor bias occurring between two countries i.e., China & USA were compared. Finally, the latent variables measured using the SCA was examined to compare audit constructs defined in earlier objectives.

## 5.2 Findings

As pointed out by Liu et al (2019), there are different risk factors associated with a garment factory. Accordingly, not all categories of SCA may be subject to the same level of bias. Since an auditor's reporting of a violation occurrence is governed by the audit protocol, it is imperative to discuss the incidence of bias in all relevant levels. Short et al (2016) states that bounded awareness may cause some auditors to over-focus on some issues and not use all available information in other cases. While it may be impossible to identify all factors that affect an auditors focus, the areas and the extent SCA categories are influenced by an auditing protocol can be identified using the research objectives in this study.

*Finding 1: Auditor bias can be found in SCAs conducted using same audit protocol*

To verify if auditor bias is present in SCAs, we analyzed the Pearson's correlation matrix, the results of Harman's test and the CFA model fit measures at both super category and SCA category level. Table 4.10 shows the correlation matrix for all super categories. High correlation between categories indicated a higher possibility of CMV. Also, from the results of Harman's test, indicated the presence of one factor which account for 70.592% of the variance of all super categories, once again suggesting that CMV is present at super category level. The unconstrained model was the best fit CFA model, indicating the CMV is present with unequal effects across super categories.

Similarly, majority of correlations at the SCA category level were also above 0.3, indicating the presence of CMV. However, Harman's single factor test, was able to explain only 37.848% of variance among the SCA categories, which is below the guidance value of 50%. From the CFA method, the unconstrained model emerged as the best fit model. It should be noted that, while Harman's test is easy to accomplish, it may not be able to detect CMV on all

occasions (Williams et al, 2010). Hence, we determine that auditor bias is present in SCAs at SCA category level. The findings for RO1 are summarized in table 5.1 below.

**Table 5.1: Findings Summary for RO1**

| Test level | Type of test | Result | Inference |
|---|---|---|---|
| Super category level | Correlation matrix | Multiple correlations above 0.3 | CMV could be present |
| | Harman's single factory test | One factor accounted for 70.592% of variance | CMV detected |
| | CFA marker variable | Unconstrained model fits best | CMV is present, with unequal effects |
| SCA category level | Correlation matrix | Multiple correlations above 0.3 | CMV could be present |
| | Harman's single factory test | One factor accounted for 37.848% of variance | CMV not detected |
| | CFA marker variable | Unconstrained model fits best | CMV is present, with unequal effects |

Within the super categories, Labor and Health & Safety super categories had auditor bias measures lower than those of entire SCA. The category of Legal & Environmental had the largest measure of method variance. For Health and Safety super category, auditor bias was measured at 3.3% of reliability, for Labor the effect of auditor bias was 9.6% and for Legal & Environmental, the effect was calculated at 42.2%

*Finding 2: The occurrence of auditor bias is not uniform across all SCA categories*

The effect of CMV on Super category and Focal SCA category occurrence rates were determined using the CFA marker variable method. Though the presence of this effect could be observed from the difference in means from summary statistics. First, separate CFA models were

analyzed by mapping each super category to only their corresponding SCA category. Models 3, 8, 13 & 17 were identified to be the best based on fit measures. Among these models, model 8 was an anomaly as it indicated that CMV effects are uniform in Health & Safety super category. In all other cases, the models were unconstrained, meaning the auditor bias effects on all levels of audit categories were unequal. *Model 3* was determined to be the most comprehensive as it contained the effects for all Super Categories and Focal SCA categories.

*Finding 3: Overall, auditor bias accounted for 11.6% of reliability in occurrence rates for the entire SCA.* .

*Finding 4: The Legal and Environmental super category is affected most by auditor bias, where 42.2% of the reliability in occurrence rates can be attributed to its effect.*

*Finding 5: The Health & Safety super category is the least affected by auditor bias, where only 3.3% of the reliability in occurrence rates can be attributed its effect.*

Model 3 findings were further utilized to compute auditor bias measures for Focal SCA categories. Since no prior study had examined the effect of auditor bias in SCAs, a comparative scaling of the effect could not be determined. Within the SCA categories, Health & Safety, Child Labor, Forced Labor, Harassment & Abuse, Non - Discrimination and Informed Workplace categories had CMV effect lower than the overall audit. All other categories viz. Freedom of Association, Hours of Work, Wages & Benefits, Women's rights & Environment had auditor bias effects greater than the whole SCA. The results of auditor bias measurements using model 3 are shown in table 4.23.

*Finding 6: More than 95% of reliability in Hours of Work, Wages & Benefits and Environment Categories could be attributed to auditor bias.*

*Finding 7: Less than 5% of reliability in Health & Safety, Child Labor, Forced Labor, Non - Discrimination and Informed Workplace categories could be attributed to auditor bias.*

Looking at the auditor bias between countries, though DS2 had data from factories in more than 80 countries, only 6 countries had more than 15 auditors which was considered as a minimum threshold for analysis using the CFA marker variable method. Among the six countries, China & USA had the most numbers of auditors at 43 and 28, respectively. The country-based comparisons are hence based on CFA marker variable models for these countries, respectively.

Comparing models 21 and 25, the auditor bias effects are unequal in both the countries. Overall, auditor bias accounted for 4.9% of reliability of occurrence rates from SCAs in China and 8.5% for SCAs in USA. This indicates that, within this auditing organization, SCAs from USA are subject to greater auditor bias than those from China. Within China, the focal SCA categories of Hours of Work, Women's rights and Wages & Benefits had the greatest effects from auditor bias. While the categories of Health & Safety, Environment, Informed Workplace, Legal Compliance, and Freedom of Association were the least affected (<1%). Besides larger effects from auditor bias, SCAs in USA also exhibited a larger range of variance. Only the category of Non – Discrimination had auditor bias effects <1%. Three categories – Child Labor, Informed Workplace & Legal Compliance exhibited had 100% of their reliability affected by auditor bias. The category of Women's Rights also had 99.7% of occurrence rates reliability affected by auditor bias. The findings of RO2 and RO3 are summarized in table 5.2.

*Finding 8: Auditor bias could affect SCAs unequally in different countries, even if organizations use the same auditing protocol.*

**Table 5.2: Auditor Bias variability across All SCAs, China & USA**

| Auditor Bias in All Focal SCA Categories (Decreasing occurrence) | | Auditor Bias in China for All Focal SCA Categories (Decreasing occurrence) | | Auditor Bias in USA for all SCA Categories (Decreasing occurrence) | |
|---|---|---|---|---|---|
| HW | 100.00% | HW | 94.70% | CL | 100.00% |
| WB | 99.90% | WR | 74.70% | IW | 100.00% |
| Env | 95.30% | WB | 50.00% | LC | 100.00% |
| LC | 54.70% | FL | 5.60% | WR | 99.70% |
| FoA | 53.80% | HA | 5.10% | HA | 33.40% |
| WR | 12.80% | ND | 2.90% | HS | 20.00% |
| CL | 4.90% | CL | 1.30% | Env | 20.00% |
| HS | 3.30% | FoA | 0.50% | FL | 10.00% |
| ND | 2.80% | Env | 0.40% | HW | 6.40% |
| IW | 0.10% | LC | 0.40% | FoA | 5.60% |
| FL | 0.00% | IW | 0.10% | WB | 2.10% |
| HA | 0.00% | HS | 0.00% | ND | 0.30% |

The CFA model utilized to analyze the audits incorporated 3 factors in accordance with the auditing protocol. Though this was the prescribed construct, it does not convey any information about the latent constructs that are naturally measured through SCAs. Hence, the results from exploratory factor analysis model (EFA) were used to validate them. From the EFA model, two latent factors emerged indicating the 3 factors construct the latent variable measurements could be different from the 3-factor construct used in the CFA model. This indicated that the audit protocol itself could have *construct bias*.

Interpretation of the EFA model was based on analysis of focal SCA category correlations and qualitative analysis of auditing methods for SCA categories. It was inferred from the EFA model that the grouping of SCA categories into factors were corresponded

to the correlation matrix. For example, Factor 1 consisted of Harassment & Abuse, non – Discrimination, Child Labor, Informed Workplace, Forced Labor, Women's rights, Health & Safety and Freedom of Association. The categories of Harassment & Abuse, Women's rights, Child Labor and Non – discrimination have the greatest number of positive correlations. The primary method of assessment for all categories in this factor was to review factory policies. Factor 1 was hence labeled Policy Compliance. Similarly, Factor comprised of Wages & Benefits, Hours of Work, Environment, Legal Compliance, Health & Safety & Freedom of Association. Auditors utilized category specific metrics/standards in order to evaluate them. Hence, we labeled Factor 2 as Objective Compliance. It was observed that there is low correlation between the categories across the latent factors measured in audits. The SCA categories of Health & Safety and Freedom of Association were common between both latent factors.

*Finding 9: SCAs measure more than one latent construct.*

*Finding 10: SCA categories within a latent construct may show high correlations*

*Finding 11: There is low correlation between SCA categories across latent constructs.*

Of the categories that were unique to each factor, Wages & Benefits, Hours of Work, Environment & Legal Compliance suggested high values of auditor bias. Similarly, the SCA categories in Policy Compliance factor all shared low auditor bias. This arrangement is shown in figure 5.1.

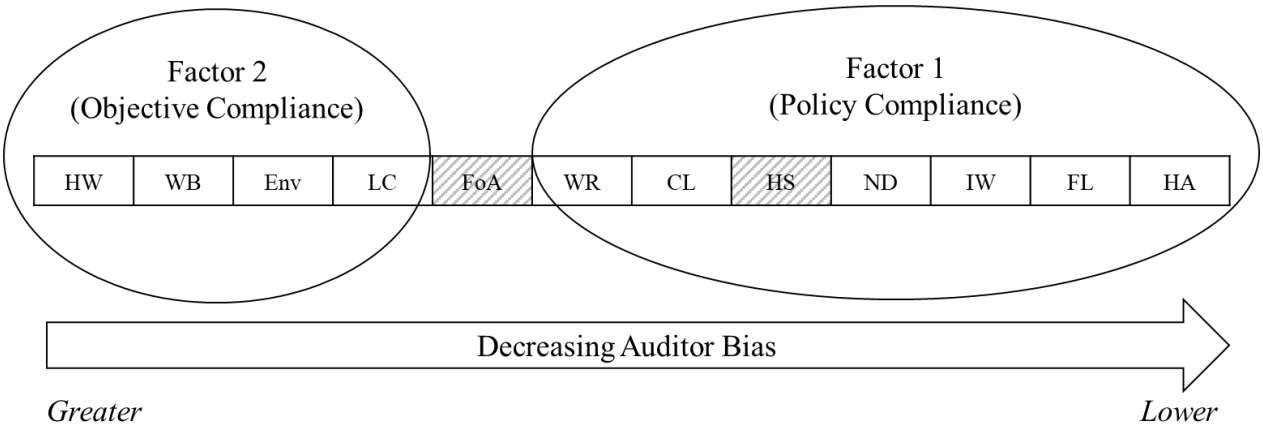


**Figure 5.1: Effect of auditor bias on latent factor groupings**

Accordingly, we provide the following finding.

*Finding 12: Auditor bias may affect latent variables measured using SCAs*

All findings for the research objectives are summarized in Table 5.3.

**Table 5.3: Findings Summary**

| Finding # | Description | Research Objective |
|---|---|---|
| 1 | *Auditor bias was found in SCAs conducted using same audit protocol* | RO1 |
| 2 | *The occurrence of auditor bias is not uniform across all SCA categories* | RO2 |
| 3 | *Overall, auditor bias accounted for 11.6% of reliability in occurrence rates for the entire SCA.* | RO1 |
| 4 | *The Legal and Environmental super category is affected most by auditor bias, where 42.2% of the reliability in occurrence rates can be attributed to its effect.* | RO2 |

**Table 5.3 (continued): Findings Summary**

| Finding # | Description | Research Objective |
|---|---|---|
| 5 | *The Health & Safety super category is the least affected by auditor bias, where only 3.3% of the reliability in occurrence rates can be attributed its effect.* | RO2 |
| 6 | *More than 95% of reliability in Hours of Work, Wages & Benefits and Environment Categories could be attributed to auditor bias.* | RO2 |
| 7 | *Less than 5% of reliability in Health & Safety, Child Labor, Forced Labor, Non - Discrimination and Informed Workplace categories could be attributed to auditor bias.* | RO2 |
| 8 | *Auditor bias could affect SCAs unequally in different countries, even if organizations use the same auditing protocol.* | RO3 |
| 9 | *SCAs measure more than one latent construct.* | N/A |
| 10 | *SCA categories within a latent construct may show high correlations* | N/A |
| 11 | *There is low correlation between SCA categories across latent constructs.* | |
| 12 | *Auditor bias may affect latent variables measured using SCAs.* | N/A |

## 5.3 Contributions and Implications

Existing literature provides for a multitude to ways to examine audits in general. Despite increased adoption by the industry, SCAs continue to be scrutinized in multiple aspects. However, few studies have analyzed the structural components of an audit in line with an auditing protocol, let alone an SCA. In this regard this study incrementally contributes to the existing body of knowledge on audits, SCAs, and CMB.

### 5.3.1 Contributions of this study

*Structured Equation Modeling technique*

A feature of this study is the use of structured equation modeling technique (SEM), in the form of confirmatory factory analysis to mimic the audit structure. The use of this technique facilitates testing multiple parsimonious relationships within the framework of an overall model (Henley et al, 2006). Since SCA's are typically used to measure multiple supplier compliance attributes, the SEM technique allows to construct equivalent models to examine multiple relationships that may exist in a SCA. To that end, the SEM modeling technique can not only be used by academic researchers, but also by industry practitioners to analyze SCAs. Some recent studies have suggested that the use of SEM technique in audits may be useful to study audit quality and organizational processes. (Azzali & Mazza, 2018; Husain, 2019).

*Relationship between SCA categories*

The examination of correlation matrices at both super category level and the focal SCA category level showed there is a possibility that the occurrence of violations between SCA categories may not be mutually exclusive. For example, the violation rates between Hours of Work and Wages and Benefits showed a correlation of 0.8352, indicating that auditors who reported high occurrences of violation in the first category, also reported high violations in the latter. Similarly, other SCA categories showed negative correlations. The correlation between Freedom of Association and Hours of Work had the largest negative correlation. This indicates that auditors who reported high occurrence of Hours of Work violations, reported low violation occurrence in the Freedom of Association category and vice versa. There were also few other SCA category pairs that showed weak or no correlations. Findings 10 & 11 help explain the

nature of SCA category correlations. A rule of thumb is that categories that show high positive correlations with others are likely more affected by auditor bias.

*Effects of auditor bias within an organization*

The results of this study demonstrate that auditor bias could decrease the reliability of SCAs within an organization. Such an effect on reliability may be unequal for the categories examined in a SCA. For the organization that was part of this study, the top 5 SCA categories that had the greatest impacts of auditor bias were: 1) Hours of Work 2) Wages & Benefits 3) Environment 4) Legal compliance 5) Freedom of Association. At the same time, the focal SCA categories that had the least impact were (in order of increasing impact): 1) Harassment & Abuse 2) Forced Labor 3) Informed Workplace 4) Non – discrimination 4) Health & Safety.

*Effect of auditor bias between countries*

Further, auditor bias appears to have unequal effects on SCAs conducted in different countries. For the same organization, in our study, it was found that SCAs conducted in China were less affected by auditor bias compared to that of USA. Auditor bias affected the reliability of SCAs in China by only 4.9%, while the same effect was 8.9% in USA. Within China, Hours of Work, Women's Rights and Wages & Benefits were the categories that showed the greatest auditor bias. On the other hand, Child Labor, Legal Compliance, Informed Workplace and Women's Rights were the categories most affected by auditor bias in USA.

The reasons for differences in auditor bias between countries could be due to differences scope of organizational maturity, effect of local laws & regulations, cultural effects and auditor training for the categories affected. For example, wider disparities in the categories of Women's rights in China & USA could exist due to differences in cultural effects

of auditors who evaluate this category. On the other hand, the disparities in the category of Hours of Work could stem from policy and documentation maturity of factories being audited in China. In case of United States, the differences that exist among local and federal laws could explain the wider variation in Legal Compliance category. Similarly, the auditing organization utilized team audits more prevalent in China than in the USA, which could also be the reason for lesser auditor bias effects in China.

*Causes of auditor bias*

This study reinforces conclusions provided by multiple other studies on the causes of auditor bias (Shore, 2008; Bettinghaus, 2014). Specifically anchoring effects stemming from code of conduct, groupthink wrought by auditing organizations and over reliance of policy related assessments, existence of multiple (and sometimes conflicting) standards between local laws and code of conduct, lack of training and references on laws and regulations. Cultural effects due to geographically varied nature of audits and the issues they examine may also play a significant role, specifically in the areas of Women's Rights, Harassment & Abuse and Freedom of Association.

### 5.3.2 Practical Implications

*Auditor Training*

Short et al (2016) in the study point out that auditors who had greater professional experience and training tend to be more effective in reporting violations. Within the realm of financial auditing in Europe, Guiral et al (2015) state that increased expertise from training can help mitigate unconscionable biases in auditors. One practical implication of our study industry practitioners is in the design more effective training programs for auditors. By providing more

training and reference materials for auditors in the countries and SCA categories where they exhibit greater bias, organizations could improve audit quality in their organizations. For instance, auditor trainings focused on scope of local laws and providing references for local laws could help auditors reduce bias in reporting issues related to Labor and Legal & Environmental category. The super category of Health & Safety contained the most detailed instructions of assessment, and showed the least bias, while the higher degree of subjectivity in other super categories could explain the higher incidence of bias in them

*SCA Teams & Focused audits*

Both Adili & Khodamipour (2018) and Short et al (2016) note that audit teams are more effective in reporting violations than individual auditors. Knowing the areas where auditors are biased can help manager design better auditing teams which could comprise of members that could balance individual biases. On the other hand, managers could also reduce auditing costs by not requiring teams to audit areas that are less affected by auditor bias. For example, in our case, audits detailing with SCA categories such as Hours of Work, Wages & Benefits and Environment would benefit more from team audits, while audits conducted for purposes of Forced Labor, Informed Workplace and Harassment & abuse may not require team audits. Companies could also split their SCA functionality into smaller focused audits, instead of one large audit. SCA categories that exhibit greater bias could be audited more frequently compared to those that exhibit less bias.

*SCA Protocol Design*

The occurrence of auditor bias is driven by an auditors' adherence to the same auditing protocol. Many companies, especially in the apparel industry today use an individual audit protocol to conduct SCAs. One potential way for organizations to reduce the

effects of auditor bias is by redesigning their protocol to include more policy measures. This is based on the finding that SCA categories that had more policy related measurement exhibited lesser bias. Companies many also benefit from having interoperability with other organization's auditing protocols.

*Remedy auditor bias*

Despite the increase in supplier compliance auditing, the activity could be affected by the presence of multiple standards and regulations which in some cases run contrary to each other. For example, categories such as Freedom of Association often involve examination of unions and collective bargaining agreements by auditors but may not always consider the functioning of unions and examination of specific cases related to labor affected by the presence or absence of one. Similarly, for the category of Wages & Benefits, the bias could arise from the dual focus on policy and objective data that need to be examined by auditors. Given the sheer volume of objective data that may be needed to be examined for this category, audit protocols tend to focus on policy related examinations leaving little room for examination of internal policy compliance by a factory. Some suggestions to reduce the bias effects could include:

1) Providing a regional certification of audits, as opposed to a global one.
2) Provide for regional variations to code of conduct in regions that display greater bias.
3) Developing a factory audit maturity model that could potentially reduce future auditing activity based on factory maturity

While the suggestions provided here could help companies reduce auditor bias, they are not likely to eliminate it entirely. However, merely the awareness of auditor bias could serve managers in making responsible business decisions based on audit reliability.

## 5.4 Future Opportunities & Limitations

An immediate opportunity emerging from this study is to examine the effects of auditor bias in SCAs undertaken using other auditing instruments and organizations. The effects of this examination could reveal the extent to which auditor bias in prevalent in SCAs. A study on auditor bias could also help clarify the areas where SCA show the greatest reliability and effect in contributing to improved supplier compliance. The study of auditor bias could also potentially be used to understand audit reliability in different countries, geographies, and industries.

This study analyzed the effects of auditor bias in only two countries. The effect of auditor bias in China was found to be lesser than in USA. This effect could be due to differences in jurisdictions and structure of applicable laws within the focal categories. Similarly, the relationship between different SCA categories could also be examined in greater detail. An understanding of causal relationships between various SCA categories could provide an emphasis for practitioners to adopt risk-based auditing approaches with suppliers and factories. The use of SEM to study violation occurrence rates at factories could also help understand risks associated with factories/factory clusters.

Lack of work in this area creates limitations for comparing the study's findings but opportunities for future inquiry. Though this study utilized a large dataset of audits, the scope was limited by the use of one audit protocol. Hence, the results from this study while applicable to one auditing organization, may differ when considering application outside of this context. Finally, the methodology adopted in this study was designed to provide understanding auditor bias due to common method variance. Additional sources of auditor bias arising from measurement and instruments design were not considered within the study, which could also

impact audit effectiveness. This limitation also presents opportunities for future research into the effectiveness and design of SCAs.

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# APPENDICES

## Appendix i: List of acronyms

**Table A1: List of Acronyms**

| Abbreviation | Description |
|---|---|
| CFA | Confirmation Factor Analysis |
| CFI | Comparative Fit Index |
| CMMI | Capability Maturity Model Integration |
| CMV or CMB | Common Method Variance or Common Method Bias |
| COC | Code of Conduct |
| CSR | Corporate Social Responsibility |
| DAX | Data Analysis Expressions |
| DEA | Data Envelopment Analysis |
| DMU | Decision Making Unit |
| EFA | Exploratory Factor Analysis |
| FoA | Freedom of Association |
| ICTI | International Council of Toy Industries |
| MAO | Modified Auditor Outcomes |
| NGO | Non – Governmental Organization |
| PDS | Primary Data Source |
| RMSEA | Root Mean Square Approximation |
| SCA | Supplier Compliance Audit |
| SDS | Secondary Data Source |
| SEM | Structured Equation Modeling |

| | |
|---|---|
| SQL | Structured Query Language |
| TLI | Tucker – Lewis Index |
| TOE | Terms of Engagement |

## Appendix ii: Q-Q plots of super category occurrence rates

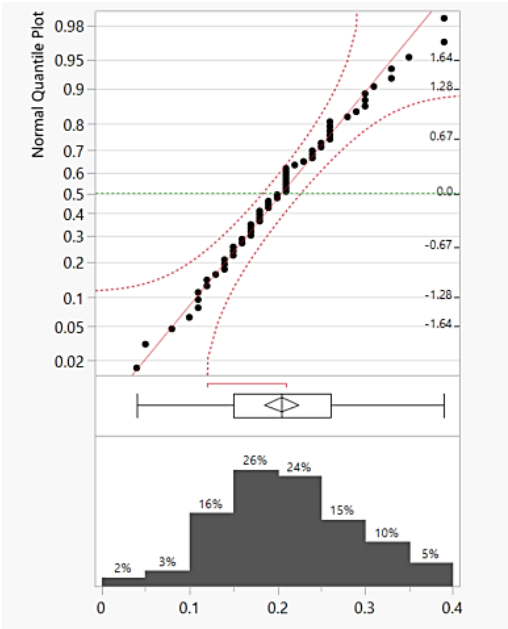


**Figure A1: Occurrence rate distribution for Health & Safety super category**

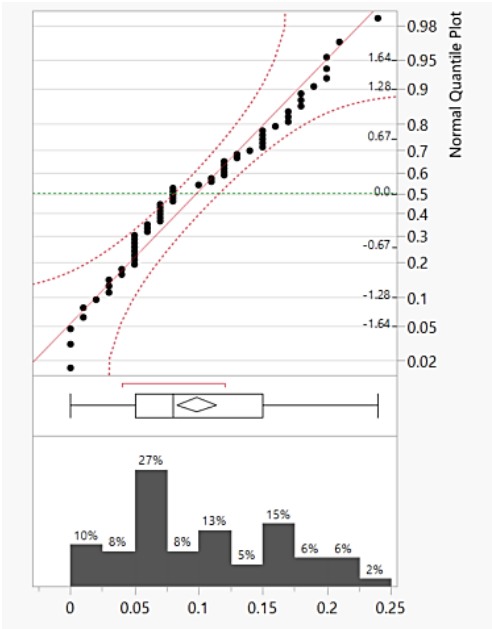


**Figure A2: Occurrence rate distribution for Labor super category**

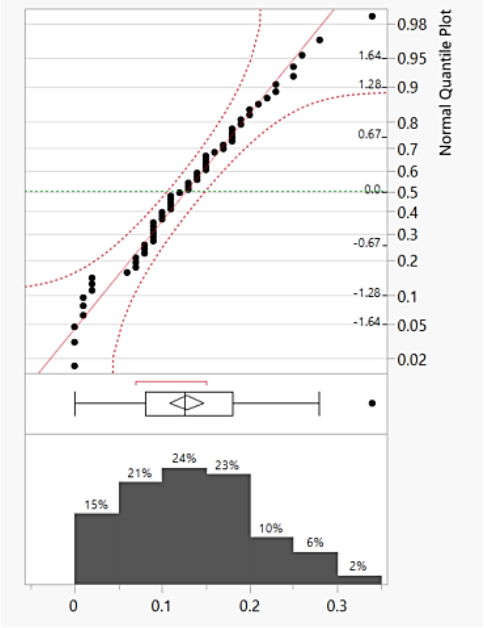


**Figure A3: Occurrence rate distribution for Legal & Environmental super category**

## Appendix iii: Q-Q plots of Focal SCA Categories

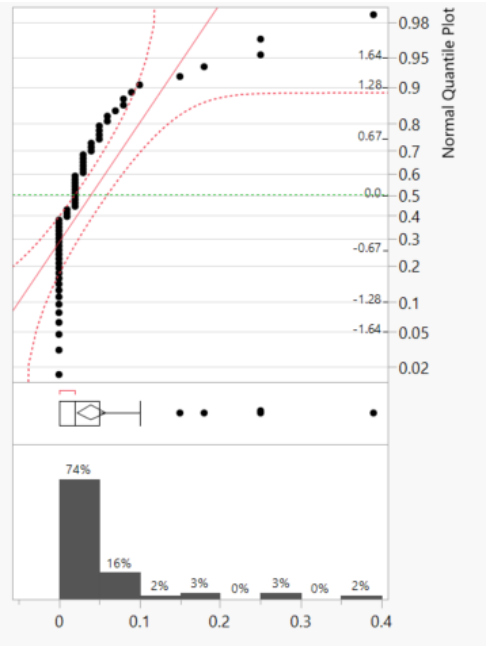


**Figure A4: Occurrence rate distribution for Child Labor category**

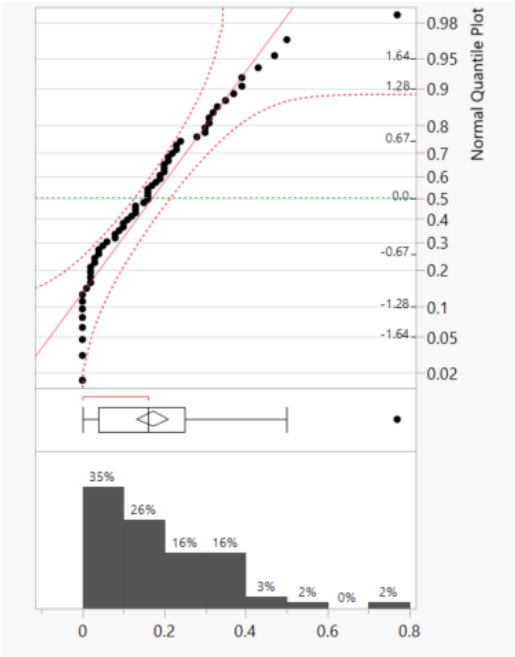


**Figure A5: Occurrence rate distribution for Environment category**

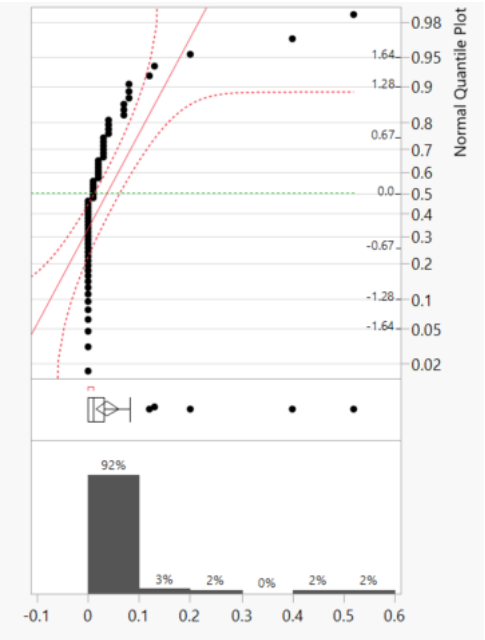


**Figure A6: Occurrence rate distribution for Forced Labor category**

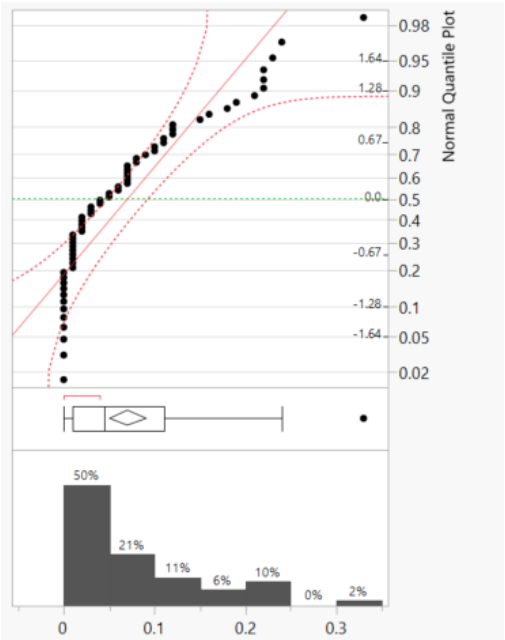


**Figure A7: Occurrence rate distribution for Freedom of Association category**

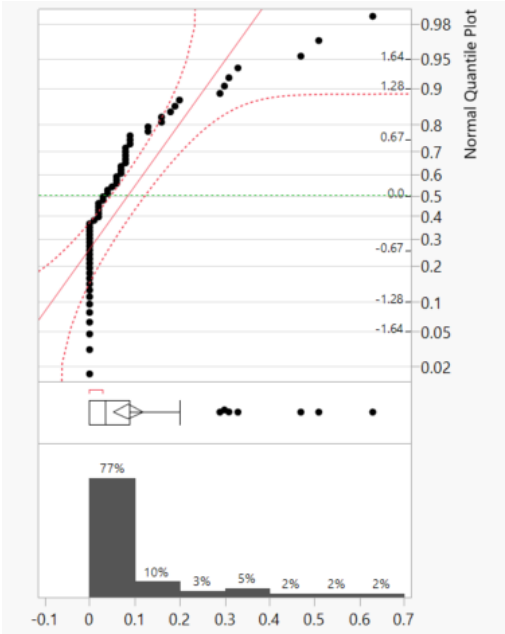


**Figure A8: Occurrence rate distribution for Harassment & Abuse category**

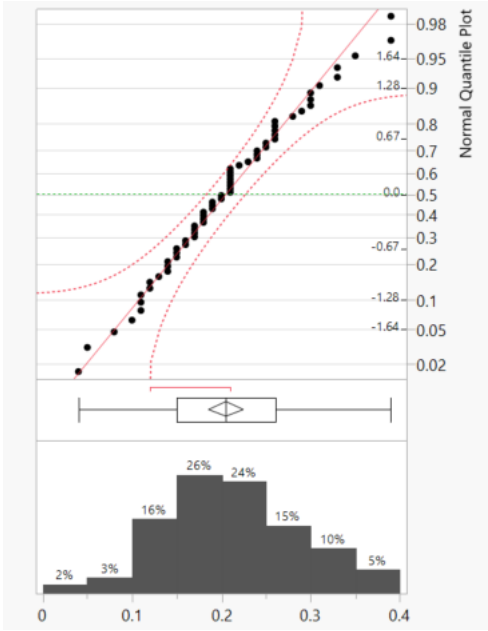


**Figure A9: Occurrence rate distribution for Health & Safety category**

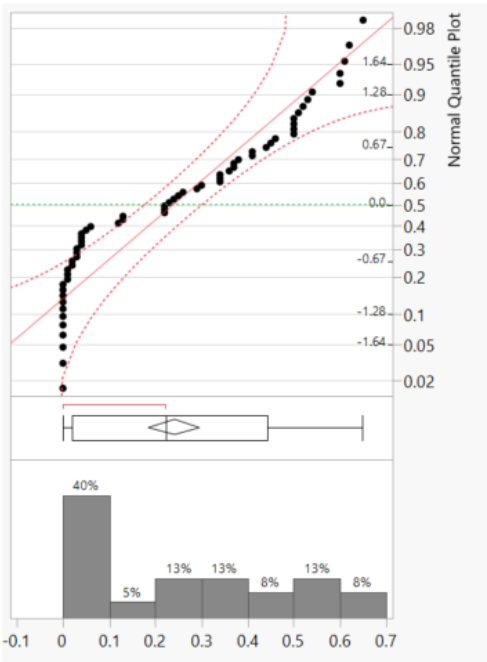


**Figure A10: Occurrence rate distribution for Hours of Work category**

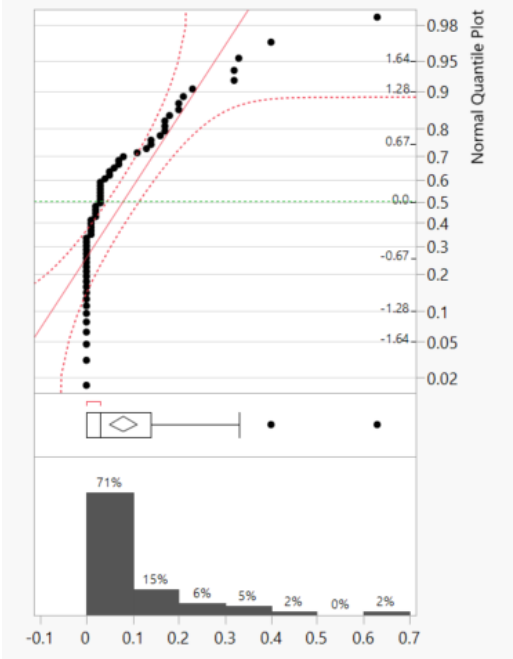


**Figure A11: Occurrence rate distribution for Informed Workplace category**

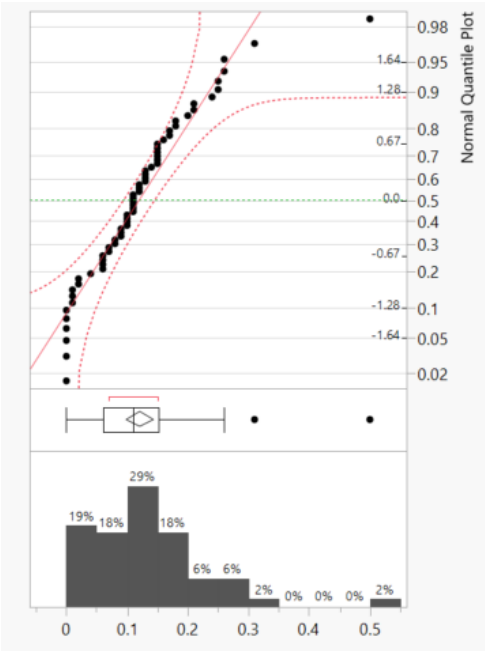


**Figure A12: Occurrence rate distribution for Legal Compliance category**

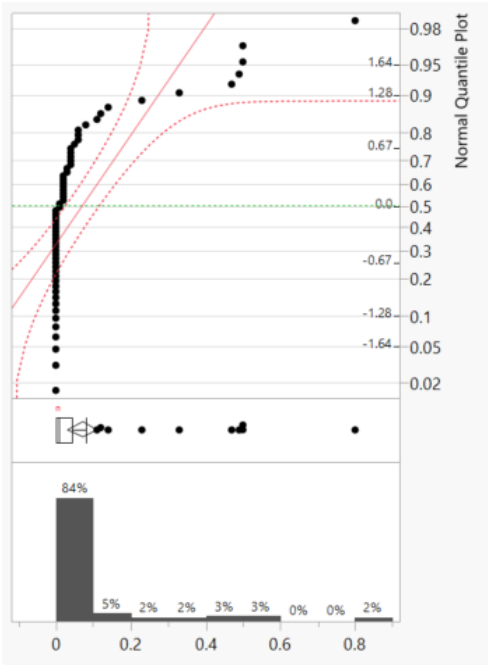


**Figure A13: Occurrence rate distribution for Non-discrimination category**

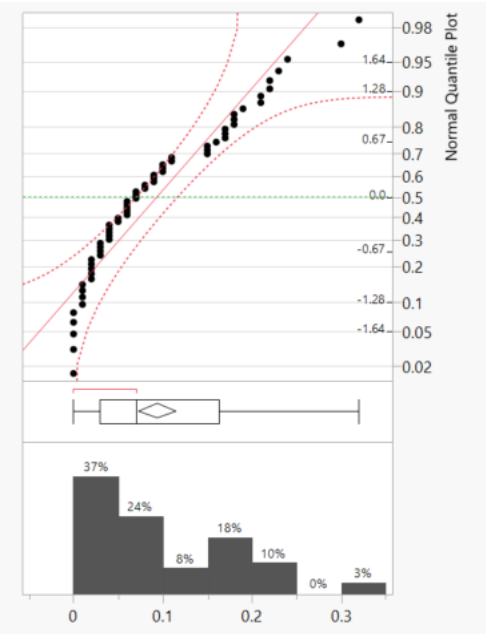


**Figure A14: Occurrence rate distribution for Wages & Benefits category**

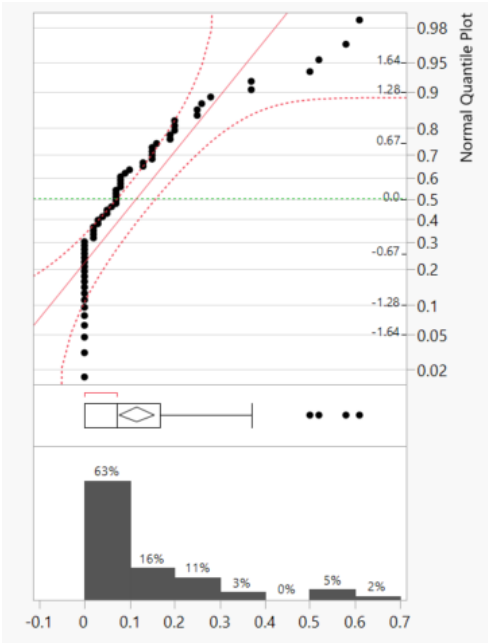


**Figure A15: Occurrence rate distribution for Women's Rights category**

## Appendix iv: R code for CFA model (RO1/DS1)

```
setwd ("C:/Users/Bala/Documents/PhD/Dissertation material/Datasets/Final
Datasets/Cleaned")
library(readxl)
library(car)
library(pastecs)
library(foreign)
library(lavaan)
library(caTools)
options(digits = 10)

# Read data frame for RQ2
rq1 <- read_excel("RQ1.xlsx")

# RQ1 CFA model HS

rq1cfahs <- 'HS1 =~ NA*HS
           MA =~ NA*M1_FC + M2_MC + M3_SC + M4_Dom + 0*HS '

model6 <- cfa(rq1cfahs, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model6, fit.measures = TRUE, standardized = TRUE)

# RQ1 Baseline model HS

rq1basehs <- 'HS1 =~ NA*HS
              MA =~ 0.944*M1_FC + 0.552*M2_MC + 0.308*M3_SC + 0.648*M4_Dom +
0*HS
              HS1 ~~ 0*MA'

model7 <- cfa(rq1basehs, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model7, fit.measures = TRUE, standardized = TRUE)

# RQ1 Constrained model HS
```

```
rq1conshs <- 'HS1 =~ NA*HS
              MA =~ 0.944*M1_FC + 0.552*M2_MC + 0.308*M3_SC + 0.648*M4_Dom +
a*HS
              HS1 ~~ 0*MA'
model8 <- cfa(rq1conshs, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model8, fit.measures = TRUE, standardized = TRUE)

# RQ1 Unconstrained model HS
rq1unchs <- 'HS1 =~ NA*HS
              MA =~ 0.944*M1_FC + 0.552*M2_MC + 0.308*M3_SC + 0.648*M4_Dom +
HS
              HS1 ~~ 0*MA'

model9 <- cfa(rq1unchs, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model9, fit.measures = TRUE, standardized = TRUE)

# RQ1 CFA model LA
rq1cfala <- 'LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
              MA =~ NA*M1_FC + M2_MC + M3_SC + M4_Dom + 0*CL + 0*FL + 0*FoA +
0*HA + 0*HW + 0*ND + 0*WB + 0*WR'

model10 <- cfa(rq1cfala, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model10, fit.measures = TRUE, standardized = TRUE)

# RQ1 Baseline model LA
rq1basela <- 'LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
              MA =~ 0.922*M1_FC + 0.514*M2_MC + 0.294*M3_SC + 0.556*M4_Dom +
0*CL + 0*FL + 0*FoA + 0*HA + 0*HW + 0*ND + 0*WB + 0*WR
              LA ~~ 0*MA'

model11 <- cfa(rq1basela, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model11, fit.measures = TRUE, standardized = TRUE)

# RQ1 Constrained model LA
```

```
rq1consla <- 'LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
              MA =~ 0.922*M1_FC + 0.514*M2_MC + 0.294*M3_SC + 0.556*M4_Dom +
a*CL + a*FL + a*FoA + a*HA + a*HW + a*ND + a*WB + a*WR
              LA ~~ 0*MA'

model12 <- cfa(rq1consla, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model12, fit.measures = TRUE, standardized = TRUE)

# RQ1 Unconstrained model LA
rq1uncla <- 'LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
              MA =~ 0.922*M1_FC + 0.514*M2_MC + 0.294*M3_SC + 0.556*M4_Dom +
CL + FL + FoA + HA + HW + ND + WB + WR
              LA ~~ 0*MA'

model13 <- cfa(rq1uncla, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model13, fit.measures = TRUE, standardized = TRUE)

# RQ1 CFA Model LE
rq1cfale <- 'LE =~ NA*Env + IW + LC
            MA =~ NA*M1_FC + M2_MC + M3_SC + M4_Dom + 0*Env + 0*IW + 0*LC'

model14 <- cfa(rq1cfale, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model14, fit.measures = TRUE, standardized = TRUE)

# RQ1 Baseline Model LE
rq1basele <- 'LE =~ NA*Env + IW + LC
            MA =~ 0.608*M1_FC + 0.282*M2_MC + 0.178*M3_SC + 0.333*M4_Dom +
0*Env + 0*IW + 0*LC
            LE ~~ 0*MA'

model15 <- cfa(rq1basele, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model15, fit.measures = TRUE, standardized = TRUE)

# RQ1 Constrained Model LE
```

```
rq1consle <- 'LE =~ NA*Env + IW + LC
            MA =~ 0.608*M1_FC + 0.282*M2_MC + 0.178*M3_SC + 0.333*M4_Dom +
a*Env + a*IW + a*LC
            LE ~~ 0*MA'

model16 <- cfa(rq1consle, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model16, fit.measures = TRUE, standardized = TRUE)

# RQ1 Unconstrained Model LE
rq1uncle <- 'LE =~ NA*Env + IW + LC
            MA =~ 0.608*M1_FC + 0.282*M2_MC + 0.178*M3_SC + 0.333*M4_Dom +
Env + IW + LC
            LE ~~ 0*MA'

model17 <- cfa(rq1uncle, data = rq1, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model17, fit.measures = TRUE, standardized = TRUE)
```

## Appendix v: R code for CFA model (RO2/DS2)

```
setwd ("C:/Users/Bala/Documents/PhD/Dissertation material/Datasets/Final
Datasets/Cleaned")
library(readxl)
library(car)
library(pastecs)
library(foreign)
library(lavaan)
library(caTools)
options(digits = 10)
# Read data frame for RQ2

rq2 <- read_excel("RQ1.xlsx")

# Test code for other files
rq1.dat <- read_excel("RQ1 super category.xlsx")

summary(rq1.dat)
#Summary statistics of RQ1
stat.desc(rq1.dat)

# Plot Histograms
hist(rq1.dat$HS)
hist(rq1.dat$HS)
hist(rq1.dat$HS)

# CFA Model
rq2cfa <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ NA*M1_FC + M2_MC + M3_SC + M4_Dom + 0*HS + 0*CL + 0*FL +
0*FoA + 0*HA + 0*HW + 0*ND + 0*WB + 0*WR + 0*Env + 0*IW + 0*LC'

model0 <- cfa(rq2cfa, data = rq2, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model0, fit.measures = TRUE, standardized = TRUE)
```

```
# Baseline model
rq2base <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.925*M1_FC + 0.496*M2_MC + 0.279*M3_SC + 0.584*M4_Dom +
0*HS + 0*CL + 0*FL + 0*FoA + 0*HA + 0*HW + 0*ND + 0*WB + 0*WR + 0*Env + 0*IW
+ 0*LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'

model1 <- cfa(rq2base, data = rq2, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model1, fit.measures = TRUE, standardized = TRUE)

# Constrained model
rq2cons <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.925*M1_FC + 0.496*M2_MC + 0.279*M3_SC + 0.584*M4_Dom +
a*HS + a*CL + a*FL + a*FoA + a*HA + a*HW + a*ND + a*WB + a*WR + a*Env + a*IW
+ a*LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'

model2 <- cfa(rq2cons, data = rq2, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model2, fit.measures = TRUE, standardized = TRUE)

# Unconstrained model

rq2un <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.925*M1_FC + 0.496*M2_MC + 0.279*M3_SC + 0.584*M4_Dom + HS
+ CL + FL + FoA + HA + HW + ND + WB + WR + Env + IW + LC
            HS1 ~~ 0*MA
```

```
            LA ~~ 0*MA
            LE ~~ 0*MA'

model3 <- cfa(rq2un, data = rq2, optim.method = "BFGS", optim.force.converged
= TRUE)
summary(model3, fit.measures = TRUE, standardized = TRUE)

# CFA expanded model
rq2cfaex <- 'HS1 =~ NA*AF + CD + CS + EE + FF + FS + SP + SE
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ NA*M1_FC + M2_MC + M3_SC + M4_Dom + 0*AF + 0*CD + 0*CS +
0*EE + 0*FF + 0*FS + 0*SP + 0*SE + 0*CL + 0*FL + 0*FoA + 0*HA + 0*HW + 0*ND +
0*WB + 0*WR + 0*Env + 0*IW + 0*LC'

model4 <- cfa(rq2cfaex, data = rq2, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model4, fit.measures = TRUE, standardized = TRUE)

# Unconstrained expanded model
rq2uncex <- 'HS1 =~ NA*AF + CD + CS + EE + FF + FS + SP + SE
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.299*M1_FC + 0.164*M2_MC + 0.089*M3_SC + 0.194*M4_Dom + AF
+ CD + CS + EE + FF + FS + SP + SE + CL + FL + FoA + HA + HW + ND + WB + WR +
Env + IW + LC'

model5 <- cfa(rq2uncex, data = rq2, std.lv = TRUE, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model5, fit.measures = TRUE, standardized = TRUE)
```

## Appendix vi: R code for CFA model (RO3/DS3 & DS4)

```
setwd ("C:/Users/Bala/Documents/PhD/Dissertation material/Datasets/Final
Datasets/Cleaned")
library(readxl)
library(car)
library(pastecs)
library(foreign)
library(lavaan)
library(caTools)
options(digits = 10)

# Read data frame for RQ2
rq3_China <- read_excel("RQ3 China Markers.xlsx")
rq3_US <- read_excel("RQ3 US Markers.xlsx")

# CFA Model China
rq3cfachina <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ NA*M1_FC + M2_MC + M3_SC + M4_Dom + 0*HS + 0*CL + 0*FL +
0*FoA + 0*HA + 0*HW + 0*ND + 0*WB + 0*WR + 0*Env + 0*IW + 0*LC'


model18 <- cfa(rq3cfachina, data = rq3_China, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model18, fit.measures = TRUE, standardized = TRUE)

# Baseline model China
rq3basechina <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.108*M1_FC + 0.087*M2_MC + 0.018*M3_SC + 0.112*M4_Dom +
0*HS + 0*CL + 0*FL + 0*FoA + 0*HA + 0*HW + 0*ND + 0*WB + 0*WR + 0*Env + 0*IW
+ 0*LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
```

```
            LE ~~ 0*MA'

model19 <- cfa(rq3basechina, data = rq3_China, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model19, fit.measures = TRUE, standardized = TRUE)

# Constrained model China
rq3conschina <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.108*M1_FC + 0.087*M2_MC + 0.018*M3_SC + 0.112*M4_Dom +
a*HS + a*CL + a*FL + a*FoA + a*HA + a*HW + a*ND + a*WB + a*WR + a*Env + a*IW
+ a*LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'

model20 <- cfa(rq3conschina, data = rq3_China, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model20, fit.measures = TRUE, standardized = TRUE)

# Unconstrained model China
rq3unchina <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.108*M1_FC + 0.087*M2_MC + 0.018*M3_SC + 0.112*M4_Dom + HS
+ CL + FL + FoA + HA + HW + ND + WB + WR + Env + IW + LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'

model21 <- cfa(rq3unchina, data = rq3_China, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model21, fit.measures = TRUE, standardized = TRUE)

# CFA Model USA
rq3cfaus <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
```

```
            LE =~ NA*Env + IW + LC
            MA =~ NA*M1_FC + M2_MC + M3_SC + 0*HS + 0*CL + 0*FL + 0*FoA +
0*HA + 0*HW + 0*ND + 0*WB + 0*WR + 0*Env + 0*IW + 0*LC'

model22 <- cfa(rq3cfaus, data = rq3_us, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model22, fit.measures = TRUE, standardized = TRUE)

# Baseline model USA
rq3baseus <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.04*M1_FC + 0.03*M2_MC + 0.054*M3_SC + 0*HS + 0*CL + 0*FL
+ 0*FoA + 0*HA + 0*HW + 0*ND + 0*WB + 0*WR + 0*Env + 0*IW + 0*LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'


model23 <- cfa(rq3baseus, data = rq3_US, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model23, fit.measures = TRUE, standardized = TRUE)

# Constrained model USA
rq3consus <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.04*M1_FC + 0.03*M2_MC + 0.054*M3_SC + a*HS + a*CL + a*FL
+ a*FoA + a*HA + a*HW + a*ND + a*WB + a*WR + a*Env + a*IW + a*LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'

model24 <- cfa(rq3consus, data = rq3_US, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model24, fit.measures = TRUE, standardized = TRUE)

# Unconstrained model USA
```

```
rq3unus <- 'HS1 =~ NA*HS
            LA =~ NA*CL + FL + FoA + HA + HW + ND + WB + WR
            LE =~ NA*Env + IW + LC
            MA =~ 0.04*M1_FC + 0.03*M2_MC + 0.054*M3_SC + HS + CL + FL + FoA
+ HA + HW + ND + WB + WR + Env + IW + LC
            HS1 ~~ 0*MA
            LA ~~ 0*MA
            LE ~~ 0*MA'

model25 <- cfa(rq3unus, data = rq3_US, optim.method = "BFGS",
optim.force.converged = TRUE)
summary(model25, fit.measures = TRUE, standardized = TRUE)
```

**Appendix vii: Table showing # of assessments and countries in SDS**

**Table A2: Number of Assessments and Countries in SDS**

| Country | # Of Assessments | # Of Factories |
|---|---|---|
| Albania | 12 | 6 |
| Argentina | 226 | 101 |
| Bangladesh | 693 | 182 |
| Belgium | 8 | 8 |
| Brazil | 636 | 241 |
| Bulgaria | 24 | 11 |
| Cambodia | 382 | 101 |
| Canada | 64 | 38 |
| Chile | 14 | 6 |
| China | 5442 | 1726 |
| Colombia | 45 | 18 |
| Costa Rica | 7 | 2 |
| Dominican Republic | 61 | 21 |
| Ecuador | 8 | 2 |
| Egypt | 105 | 40 |
| El Salvador | 94 | 27 |
| France | 5 | 1 |
| Georgia | 3 | 1 |
| Germany | 5 | 4 |
| Greece | 24 | 8 |
| Guatemala | 192 | 49 |
| Haiti | 40 | 12 |
| Honduras | 49 | 17 |
| Hong Kong | 91 | 88 |
| India | 1307 | 349 |
| Indonesia | 316 | 86 |
| Italy | 169 | 126 |
| Japan | 173 | 58 |
| Jordan | 28 | 10 |
| Kenya | 46 | 18 |
| Korea, Republic of (South Korea) | 103 | 51 |
| Macao | 8 | 7 |
| Madagascar | 2 | 2 |

| Country | # Of Assessments | # Of Factories |
|---|---|---|
| Mauritius | 49 | 15 |
| Mexico | 556 | 170 |
| Moldova, Republic Of | 42 | 9 |
| Morocco | 9 | 6 |
| Myanmar | 31 | 9 |
| Netherlands | 2 | 2 |
| Nicaragua | 85 | 24 |
| North Macedonia | 38 | 9 |
| Pakistan | 245 | 84 |
| Panama | 2 | 2 |
| Peru | 36 | 17 |
| Philippines | 214 | 64 |
| Poland | 11 | 5 |
| Portugal | 157 | 60 |
| Puerto Rico | 4 | 3 |
| Romania | 58 | 29 |
| Samoa | 4 | 4 |
| Slovenia | 13 | 4 |
| South Africa | 29 | 14 |
| Spain | 9 | 3 |
| Switzerland | 2 | 2 |
| Taiwan | 303 | 133 |
| Thailand | 240 | 67 |
| Tunisia | 47 | 30 |
| Turkey | 530 | 199 |
| Ukraine | 2 | 1 |
| United Arab Emirates | 17 | 8 |
| United Kingdom | 17 | 17 |
| United States of America | 1026 | 541 |
| Unknown | 2 | 1 |
| Venezuela | 27 | 9 |
| Vietnam | 1519 | 421 |
| Virgin Islands, British | 17 | 17 |