Production and Operations Management

How Digital Technologies Impact Tolerance to Modern Slavery in Supply Chain Networks: An Institutional Theory Perspective

This study develops a socio-technical model to understand the tolerance level of modern slavery in firms across supply chains. The regulative, mimetic and normative pressures have been incorporated as network characteristics induced by digital technologies. Our model institutionalizes the role of digital technology in transforming these pressures to affect the tolerance to modern slavery. We have combined agent-based simulation on networks, adopting a complex system perspective, with discrete choice methods, an established economic theory, for simulating numerous organizational choices with respect to tolerance level as a function of network pressures to model tolerance of modern slavery in supply chain network. We studied the impact of organization-specific and general-purpose technologies on tolerance due to their effect on each kind of pressure. Our findings suggest that the proposed simulation model with network pressures based on empirical data captures the real-world tolerance distribution and tolerance in the supply chain network is sensitive to each kind of technology. The sensitivity of tolerance is highest in response to the organization-specific digital technology inducing regulatory pressure, followed by general-purpose technology affecting normative pressure.

Key words: Institutional Theory, Tolerance, Digital Technology, Supply Chain Network, Simulation Model, Modern Slavery

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1 Descriptive Statistics and Visualization of Tolerance

	Commitment and Governance	Traceability and Risk Assessment	Purchasing Practices	Recruitment	Worker Voice	Monitoring	Remedy
Commitment and Governance	1	0.774	0.691	0.859	0.712	0.712	0.834
Traceability and Risk Assessment	0.774	1	0.56	0.777	0.699	0.699	0.837
Purchasing Practices	0.691	0.56	1	0.65	0.627	0.627	0.632
Recruitment	0.859	0.777	0.65	1	0.798	0.798	0.806
Worker Voice	0.712	0.699	0.627	0.798	1	1	0.724
Monitoring	0.712	0.699	0.627	0.798	1	1	0.724
Remedy	0.834	0.837	0.632	0.806	0.724	0.724	1
Min	0	0	0	0	0	0	0
1st Quartile	42	6.25	9.167	3.75	4.167	4.167	6.25
Median	52	25	20.833	26.25	7.5	7.5	18.75
Mean	54.39	35.84	21.259	27.32	12.449	12.449	29.78
3rd Quartile	70	62.5	25.833	36.25	14.167	14.167	50
Max	98	93.75	69.167	77.5	63.333	63.333	87.5

Table 1 Correlation and descriptive statistics of the indicators for iolerance to modern slavery Source: Dataset on ICT companies, KnowTheChain (2021)

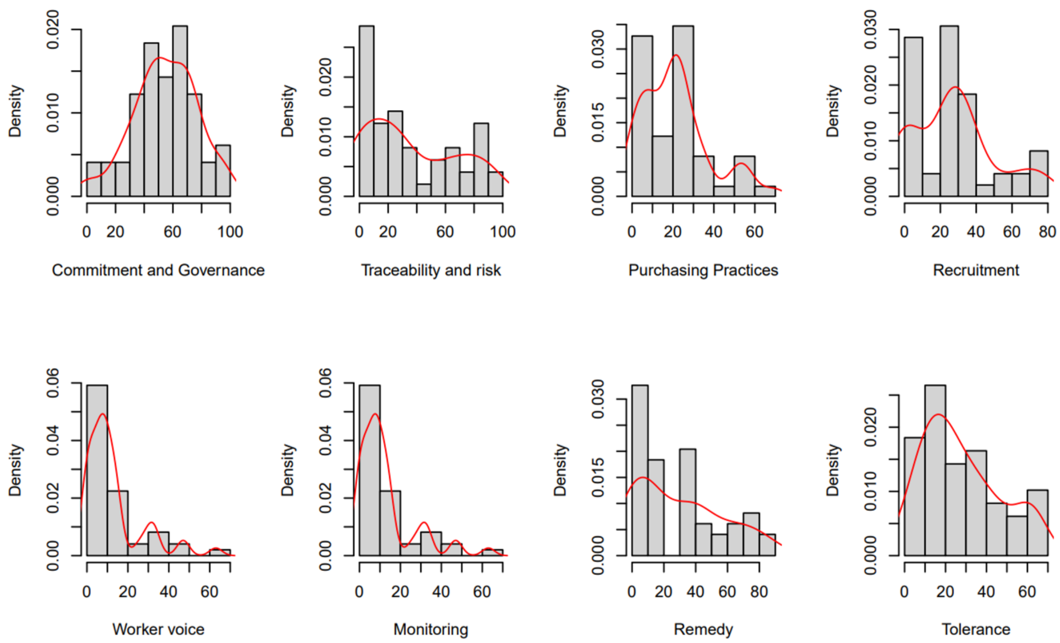

Figure 1 Distribution of tolerance to modern slavery and its indicators. Source: Dataset on ICT companies, KnowTheChain (2021)

2 Bayesian Networks

A Bayesian network is a Directed Acyclic Graph (DAG) containing nodes representing random variables and directed arcs representing dependencies. The DAG of the Bayesian network is a factorization of the joint probability distribution into the local probability distribution of each variable. The factorization is directed by the Markov property of Bayesian networks, which assumes that every node/random variable is directly dependent only on its parent nodes (Heckerman 2008)

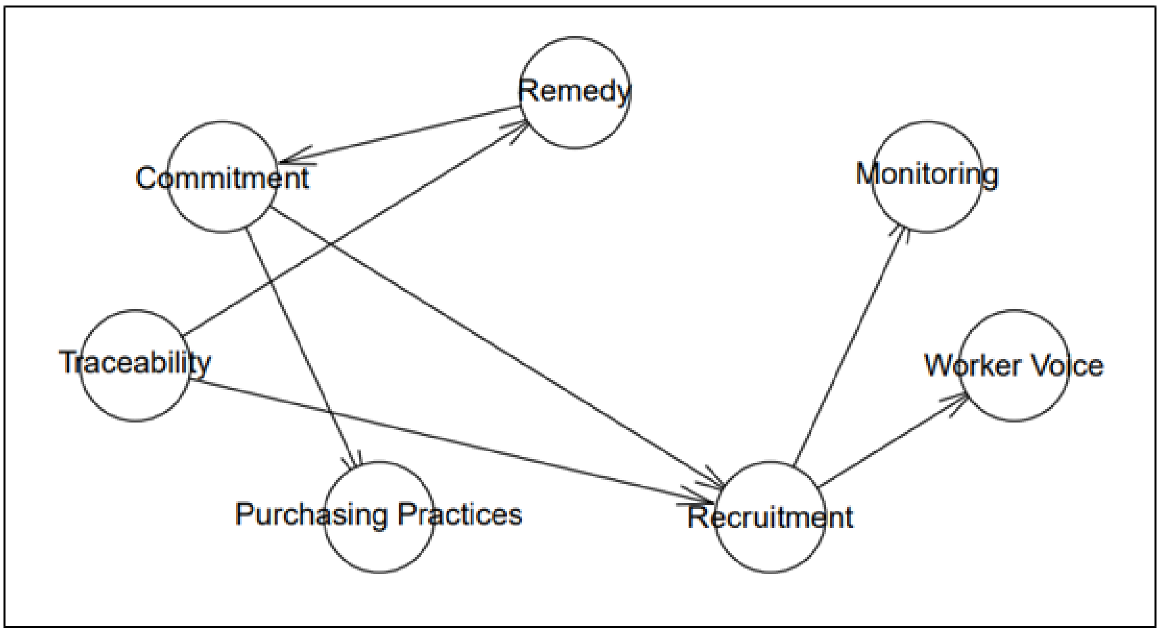

Figure 2 Bayesian network representing factorization of joint distribution of the indicators of tolerance to modern slavery into local distributions

We choose Gaussian Bayesian network modelling, where the joint distribution of indicators is assumed to be a multivariate normal distribution. The DAG learnt there is a factorization of their joint distribution into normally distributed and linearly dependent local relationships. We used a score-based hill-climbing algorithm as detailed by Gámez et al. (2011) for structure learning, where a possible solution is generated and evaluated for minimum Bayesian Information Criteria (BIC) iteratively. The structure learnt and the estimated parameters among the indicators are as shown in the Figure 3 and Table 2 respectively.

IND	REM	COM	PUR	RC	TR	WV	MON	Intercept
REM	0	0	0	0	0.72	0	0	4
COM	0.67	0	0	0	0	0	0	34.07
PUR	0	0.51	0	0	0	0	0	-6.49
RC	0	0.65	0	0	0.2	0	0	-15.6
TR	0	0	0	0	0	0	0	35.91
WV	0	0	0	0.48	0	0	0	-0.72
MON	0	0	0	0.48	0	0	0	-0.72

Table 2 Bayesian network parameters representing local dependencies among the indicators of tolerance of modern slavery: Remedy (REM), Commitment (COM), Purchasing Practices (PUR), Recruitment (RC), Traceability (TR), Worker Voice (WV) and Monitoring (MON)

The observation of Q-Q plot of residuals for each model shows that the residuals are approximately normal as desired.

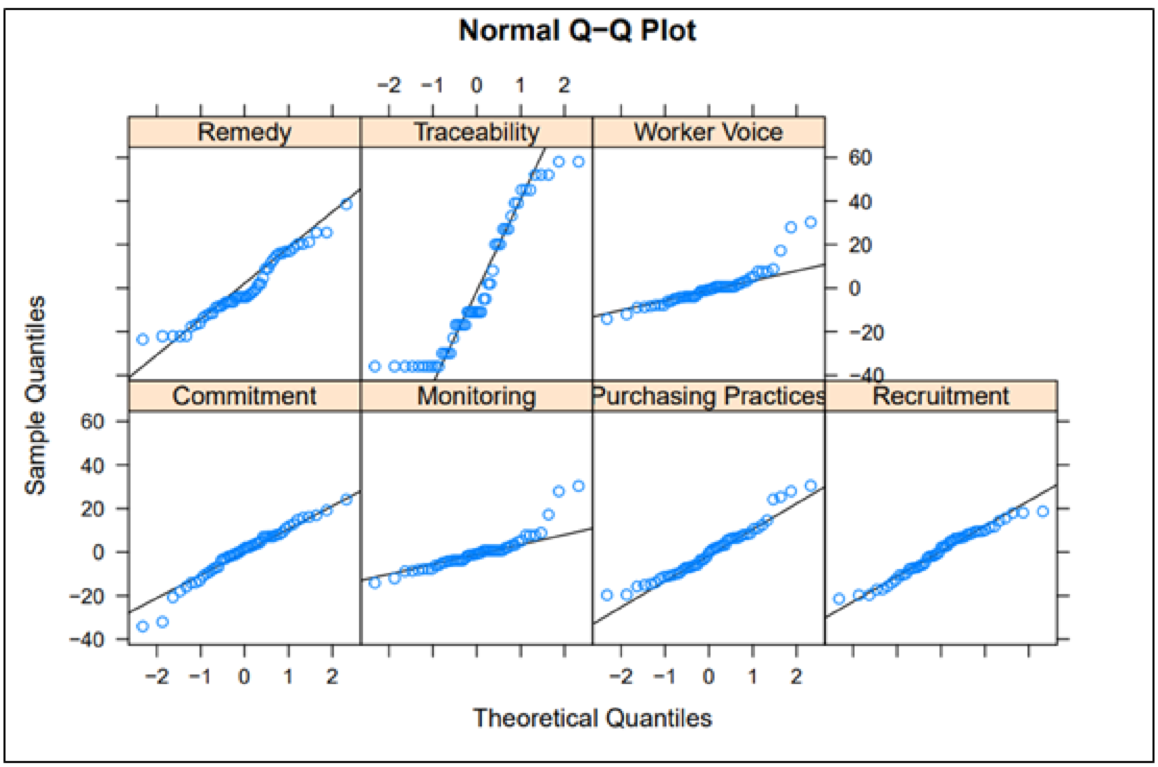

Figure 3 Normal Q-Q plot between theoretical quantiles and residuals of the liner model at each node in the Bayesian network

3 Characteristics of Supply Chain Network

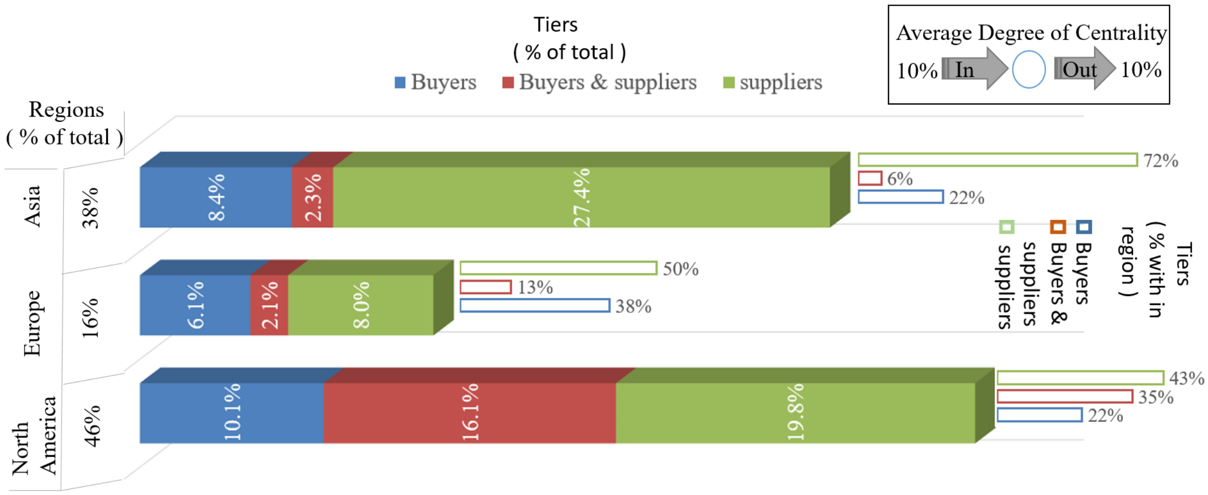

Figure 4 Network description of organizations in supply chain network across the world: Size of each of 3 regions and 3 tiers as a percentage of total organizations, size of each of 3 tiers as percentage within each region, average in and out degree of centrality. Source : Dataset on ICT companies, KnowTheChain (2021)

The characterization of the complex real-world network can be analyzed using clusters, scaling, centrality and distances as discussed by García Robledo et al. (2016) in Buyya et al. (2016). Clustering refers to the number of groups or communities of actors that might be present in the network. The edges between actors represent interactions and are dense within and sparse between the communities. These communities often have complex hierarchical connectivity among actors. A distance separates the actors in a network, and this distance is not necessarily physical but rather a function of attributes of each actor.

4 Assumptions of Error Components

Luce and Suppes (1965) and McFadden (1973) show that the logit formulation implies that $\varepsilon^{i,n}$ is extreme value distributed. McFadden and Train (2000) notes that the extreme value distributed random utility model has limited practical application because of the difficulty of specifying and estimating abstract, generalized extreme value distribution. Train (2009) notes that the assumption of extreme value distribution for errors is approximately the same as assuming an independent normal distribution. The extreme value distribution has slightly fatter tails than the normal distribution, but the shape does not vary significantly. Moreover, the main assumption is about the independence of error between alternative choices but not the shape. We have avoided the independence or IIA(irrelevant alternatives) assumption of multinomial logit models so that the organizations can switch between the choices that possess more value (Fiebig et al. 2010). So, $\eta^{i,L,j}$ and $\eta^{i,G,j}$ are assumed to be multivariate normally distributed and $\varepsilon^{i,n}$ is assumed to be normally distributed.

5 Initialization and Validation

5.1 Initialization

Agent-based models typically use standard random distributions for initial condition values in simulations. Banks (2005) discussed a whole host of statistical distributions that can be used for input modelling for simulation. Hassan et al. (2010) note that the random uniform distribution is the most popular choice for initialization. The standard procedure is to run a series of simulations with chosen random distribution, for instance, random uniform, and compare the outcome. They note that it is not to say that the outcome can't be improved with other random distributions, and random uniform can be a poor choice sometimes. They also note that Gaussian or random normal distribution can sometimes improve the output. Suppose the data exists from either survey or other data collection processes. In that case, they recommend using analytically or empirically fitted distribution for initial values, especially in comparison of terminal simulation outcome with real-world values is desirable.

We fitted the tolerance data with random uniform, random normal and beta distribution. We fitted beta distribution in addition to former distributions as the initial visualization of tolerance showed that the data is skewed from standard normal pattern and seems to be bi-modal. Beta distribution is a flexible distribution useful in fitting such skewed and bi-modal data. It has a finite range of (0,1) but in practice it is used to fit for different ranges as well by scaling. Banks (2005) show the way to transform data to fit beta distribution and transform back fitted data to original scale by creating a new random variable.(C = a +(b-a)×D, where D is in range(0,1) and C is in range(a,b)). Beta (1.63, 0.31) fitted our data better than former distributions.

We used beta distribution to initialize tolerance score for agents. However, we used beta (1.1, 0.5) instead of the perfect fit. Hassan et al. (2010) note that the selection of distribution informed by data improves output, meaning it could reduce the time it takes for the model to move in the direction of real world data. If the real world data was an outlier then the outcome may not match despite the model representing real social process. In light of this observation, we took the opportunity to choose beta distribution with slightly different parameters and significantly different cumulative density function (CDF) to verify whether the data is an outlier. We used

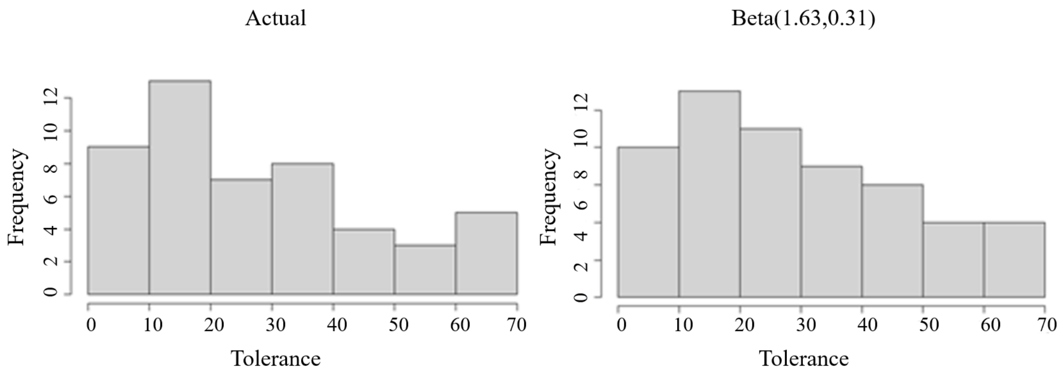

Figure 5 Actual tolerance score distribution and best fit beta distribution of tolerance

Kolmogorov–Smirnov distance to judge the fitness of fitted distribution and difference of selected distribution from the fitted distribution. We also ran pilot with fitted distribution to verify to ourselves that the possible delay or failure, if occurs, in emergence of similarity with real world data is due to data being an outlier but not because of model.

Hassan et al. (2010) state that studying networks of any kind is impossible in most scenarios as the data about interconnections between agents is missing. In our case, KnowTheChain[1] data does include the adjacency matrix of the network of agents but does not include any explicit quantitative data about the edges. We formulated our simulation to include a measure of distance between agents and we used cosine distance between the vectors of indicators of tolerance from the survey to represent similarity between agents. We used the fitted Bayesian network, as described in an earlier section, for the joint distribution of indicators to draw samples of the same, for each agent in the network. We only accept the sample of indicators that average out to the tolerance score drawn from beta distribution to maintain the definition of tolerance score.

We also need to create initial network topology among agents. The complex real world network topology can be traversed and understood using the demographic separations, abstract communities, hierarchy, hubs and centrality etc., as laid out by García Robledo et al. (2016) in (Buyya et al. 2016). Hagberg et al. (2008) provide a summary of NetworkX implementations of graph algorithms used to summarise and generate graphs with above listed characteristics. We used random partition graph generators from NetworkX for emulating the real world network characteristics detailed earlier.

[1] `https://knowthechain.org/benchmark-methodology/`

5.2 Stylized Facts

In a social system, micro level interactions of agents are directed by same or similar behavioral rules and they result in a macro level patterns or stylized facts of the system (Gilbert and Conte 1995). Agent based simulation models help in characterizing the relationship between micro level behavior and macro level patterns. Thus the model's agreement with macro level patterns of real world is a good indicator of success of the simulation (Gilbert and Terna 2000). We used the global tolerance distribution in our network as the element of comparison. In addition to global, we also looked at the lower levels of hierarchy based on the network characteristics for comparison. The observation and comparison at multiple levels of tolerance distribution is important as some models could lead to high distributional similarity globally while they are highly dissimilar in one or more lower levels. We considered the tolerance distribution for three regions, three market capitalization levels and three tiers of the organizations for comparison of simulated and real data.

5.3 Similarity Measure

There are several similarity measures between probability distributions (Gibbs and Su 2002) like Kullback-Leibler(KL) divergence, Kolmogorov–Smirnov(KS) distance and Wasserstein distance (Earth mover distance/EMD). KL divergence is an information theoretical perspective on loss of information when one probability distribution is replaced by another one and is not symmetric. KS distance is the maximum vertical distance between two probability distributions and is sensitive to location. Wasserstein distance relates to the area between two distributions as it considers the geometry of the objects like distributions. It is desirable to have a comparison of two objects like distributions that gives a similar object representing difference between two objects. Wasserstein distance has the same units as the compared items themselves (Villani 2021, Kolouri et al. 2017). Briani et al. (2016) show the usage of Wasserstein distance for distributional similarity in large networks. The minimum Wasserstein distance has come to usage and is recommended vastly in machine learning to replace maximum likelihood for inference in simulations (Bernton et al. 2019) when Bayesian approximation is not possible or computationally costly. Though we did measure KS- distance, we also choose Wasserstein for its properties and easy interpretation for calibration.

5.4 Calibration of Model Parameters

McFadden and Train (2000) observe that practical ways of choosing parsimonious mixing families of distributions for parameters and an idea of required number of samples needed for approximating choice probability distribution is necessary. They note that random coefficients following factor analytic structure with relatively simple mixing families are sufficient to approximate complex heterogeneity. They proposed using importance sampling which requires assumption or knowledge of prior distribution of parameters, indicating specific area of sample space with more impact on outcome. They also state that in principle, one can use a good specification of parameter samples for following a fully non-parametric approach of estimating utility parameters. But, in the absence of knowledge of prior distribution and/or high dimensional space sampling is intractable and results in computationally inefficient solutions as noted by Salle and Yıldızoğlu (2014). For instance, in our case we do not have any knowledge of prior distribution of the parameters W^j and α^j over sampling space (0,1). The parameters W^j are additionally constrained by $\sum_j W^j = 1$. Even if we choose a small set of 10 values for each of the parameters, we end up with at least 10^{21} scenarios as W^j is set of three dependent weights for each of the region-market capitalization groups. If we were to randomly sample Nn (N:number of samples and n:number of parameters) samples jointly , we might miss covering all the area of sampling space.

5.5 Efficient Sampling of Parameter Space

McKay et al. (2000) discuss representativeness of samples of the parameter space by comparing random, stratified and Latin hyper cube sampling (LHS) (Stein 1987). Fagiolo et al. (2019) summarise latest validation methods for agent based models in economics and includes LHS.Salle and Yıldızoğlu (2014) proposed using LHS for parameters and discusses the advantages compared to traditional sampling methods in representativeness and parsimony.

LHS enables generation of a sample size of Nn independent parameters. In LHS, the sampling region is segmented by dividing the range of each independent parameter into N non-overlapping intervals using equal probability for each interval. One value from each interval is selected at random with respect to the probability density in the interval. The N values selected at random from each interval of first parameter are combined at random with the N values of second parameter and so on for all parameters. This set of Nn-tuples is the Latin hypercube sample. Further , a modified version of Latin hyper cube sampling with dirchlet correction (LHS-D/DLHS), as described by Sun (2014), can be used for sampling W^j and regular version for α^j. In this case, the weights are sampled from LHS first and rectified using dirchlet distribution with an additional hyper parameter for controlling whether the weights with in a sample are distributed sparsely, densely or symmetrically (Sun 2014). We use the dirchlet corrected LHS instead of normalized LHS for satisfying the $\sum_j W^j = 1$ constraint as space filling property of LHS might be shrunken or lost when normalizing LHS samples directly.

Salle and Yıldızoğlu (2014) talks about required number of LHS samples for identifying range of non-linear dynamics across sample space for given number of parameters. They mention that

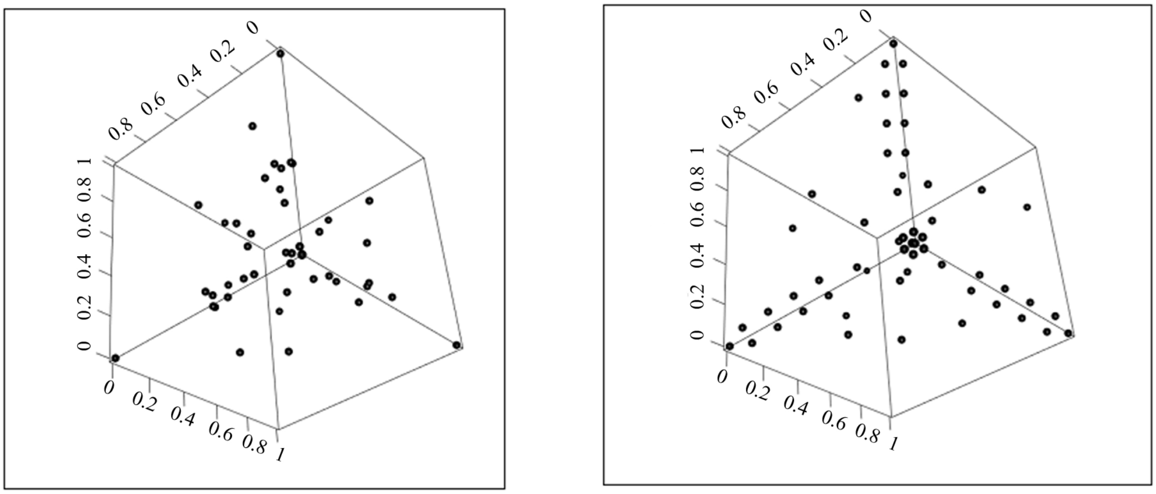

Figure 6 Dirchlet Corrected Random Latin Hypercube (DLHS/LHS-D) and LHS sampling for W^j and α^j respectively

they required 129 simulations for 22 parameters and 257 simulations for 29 parameters. Though we have 30 parameters, 9 sets of parameter vectors of length 3 are dirchlet distributed within each set, meaning that the variation of 3rd parameter is not independent from first 2 in each set. So, we can say that 21 parameters are varying independently across sample space nudging us to run at least 129 simulations to be confident. We decided to run simulations for 180 samples of 30 parameters (180×30), drawn from standard LHS samples first and then rectifying each set of W^j using dirchlet distribution. The Figure 6 only shows 10×3 dimensional space of LHS-D/DLHS of W^j and LHS of α^j because of space and dimensionality constraints. It is good to note the space filling properties of LHS even for a small 10×3 samples in parameter space.

5.6 Visualization of Tolerance Distributions of Calibrated Model

For the calibrated model parameters, the simulation's distributional similarity can be observed in the Figure 7 of CDF's at multiple levels of hierarchy. We also looked at distributional similarity at global level and found that the simulation is producing very similar CDF as shown in the Figure 7. Now that we have calibrated our model, we can simulate hypothetical scenarios for technological impacts.

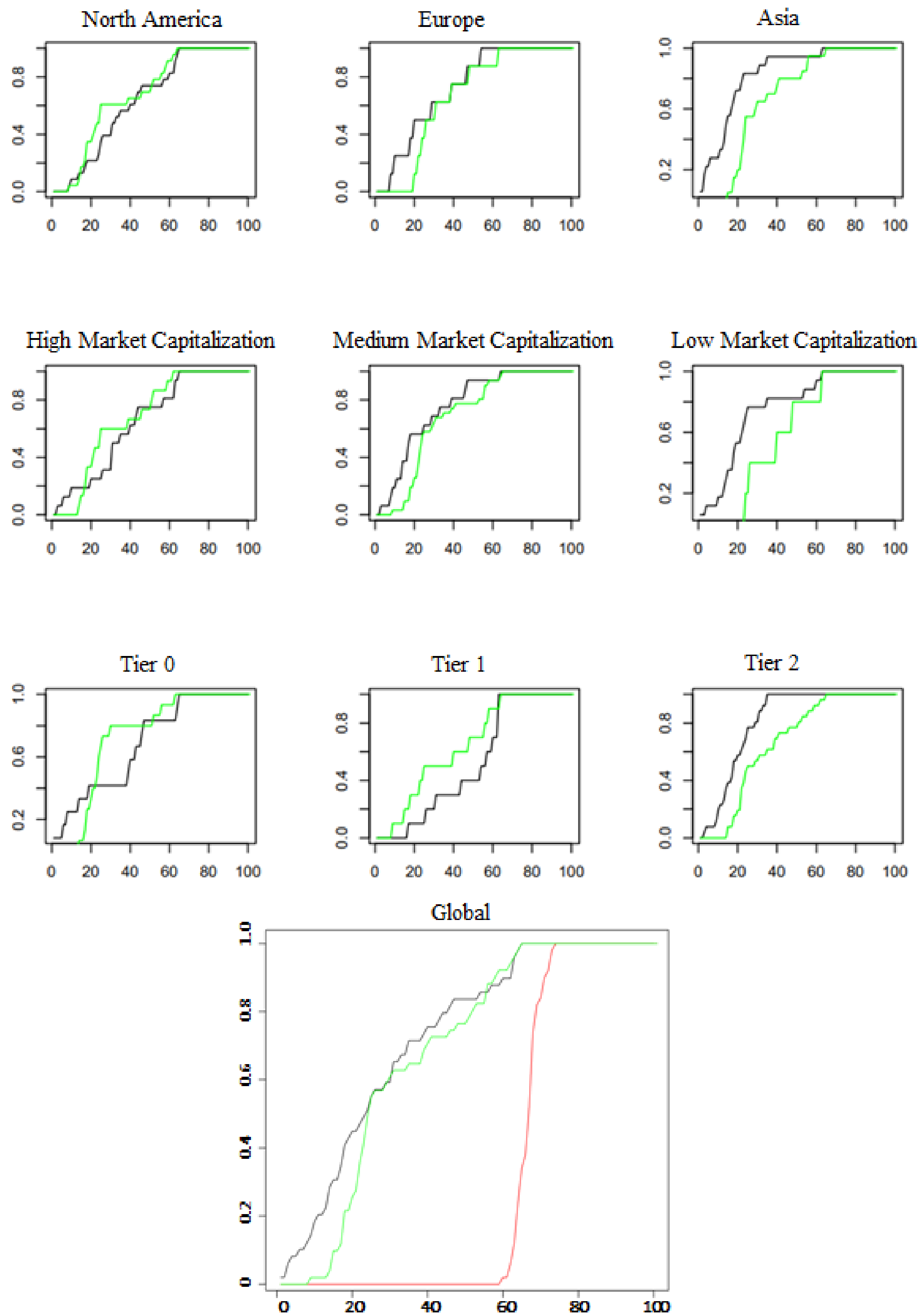

Figure 7 Similarity of simulated and real tolerance distributions. Red: Initial CDF, Green: Final CDF and Black: Real CDF (CDF: Cumulative density function)

6 Tables

This section presents the tables on key constructs conceptualised in the research paper. Table 3 summarises the legislation and international accords on modern slavery. These laws exert formal regulatory pressure on the organizations that fall under their radar. Table 4 presents the conceptualisation of the regulative, mimetic and the normative pressure from the literature. it also presents our socio-technical perspective on pressure as a network characteristic. Table 6 and Table 5 discuss the indicators on tolerance to modern slavery. It gives the organizational and employee perspective necessary to measure the level of tolerance in organizations across the supply chain.

Acts on Modern Slavery	Background	Specifications
California Transparency in Supply Chains Act	Enacted in 2011 and in effect from 2012, requires large firms (those with annual worldwide gross receipts larger than $100 million and annual Californian sales larger than $500,000) to make public declaration of their efforts towards eradicating human trafficking and slavery from its supply chain, and to publish the information on their websites	Verify supply chains relative to slavery and human trafficking risk, and whether the verification was performed by a third party; conduct audits of suppliers to ensure compliance with company standards on slavery and human trafficking; require direct suppliers to certify materials incorporated into the products comply with the laws of their country; maintain standards and procedures for employees or contractors failing to meet company standards; provide training on slavery and human trafficking issues to employees and managers
The UK Modern Slavery Act	Enacted in 2015, requiring companies to prepare and make publicly available a statement every financial year that explains the steps taken to ensure that slavery is not taking place in any of its supply chains	The statements published by the companies might include details of the organization structure, business and supply chain; organizational policies on slavery and human trafficking; due diligence processes; an acknowledgement of the parts of the supply chain that are vulnerable and the steps taken to assess and manage risk; an assessment of the effectiveness of actions taken; and details of the training offered on modern slavery and human trafficking.
International Labour organization	Their definition concentrates on the elements of modern slavery associated with forced labour within a supply chain. The ILO (2005) has identified six indicators of forced labour which they use in their study	Threats or actual physical harm to the worker; restriction of movement and confinement (to the workplace or to a limited area); debt bondage, where the worker works to pay off a debt or loan, and is not paid for his or her services; withholding of wages or excessive wage reductions that violate previously made agreements; retention of passports and identity documents so that the worker cannot leave or prove his/her identity and status; threat of denunciation to the authorities, where the worker is in an irregular immigration status.

Table 3 This table gives a brief of the major acts and legislation on Modern Slavery

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Regulative Pressure	Normative Pressure	Mimetic Pressure	Reference
It results from both formal and informal pressures exerted on organizations by other organizations upon which they are dependent and by cultural expectations in the society within which organizations function	It stems primarily from professionalization. Professionalization is the collective struggle of members of an occupation to define the conditions and methods of their work, to establish control and a cognitive base for legitimacy	When an organization faces a problem with ambiguous causes or unclear solutions or when the environment creates symbolic uncertainty, organizations may model themselves on other organizations	DiMaggio and Powell (1983)
The institutional logic underlying the regulative pillar is an instrumental one: Individuals craft laws and rules that they believe will advance their interests, and individuals conform to laws and rules because they seek the attendant rewards or wish to avoid sanctions	Normative systems are typically viewed as imposing constraints on social behaviour, it includes both values and norms. Values are conceptions of the preferred or the desirable together with the construction of standards to which existing structures or behaviours can be compared and assessed. Norms specify how things should be done; they define legitimate means to pursue valued ends	Internal interpretive processes are shaped by external cultural frameworks	Scott (2001)
The regulative pressure is exerted by focal organizations that act as agents of legislative bodies and hold their suppliers accountable. In turn, the suppliers at tier one seek compliance from the sub-suppliers in their chain. Hence, to account for this the parent nodes to a particular organization at any tier are considered.	The normative pressure in our network is believed to be a global force in which all the organization are held accountable to certain norms established by stakeholders. To account for this, our network considers each node in the supply chain irrespective of region, tier or association and their distance from each other.	The mimetic pressure is exerted by organizations at the same tiers in a supply chain. Thus, our formulation takes into account the nodes in a particular tier (nodes in tier one, nodes in sub-supplier tier, focal organizations) and their distance from each other to measure the influence each firm can have on the other firm	Conceptualisation of Pressure as Network Characteristic

Table 4 This table gives the conceptual definition of the three types of institutional pressures

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Indicator	Parameters	Definition
Commitment and Governance	Commitment	The company publicly demonstrates its commitment to addressing forced labor and human trafficking.
	Supplier Code of Conduct	The standard should be easily accessible on the company's website, is regularly updated, is communicated to the company's suppliers, and requires suppliers to cascade the standards to their own suppliers.
	Management and Accountability	The company has established clear responsibilities and accountability for the implementation of its supply chain policies that address forced labor and human trafficking, both within the company and at the board level.
	Training	The company takes steps to ensure that relevant decision-makers within the company and in different tiers of its supply chains are aware of risks related to slavery are effectively implementing the company's policies.
	Stakeholder Engagement	The company engages with relevant stakeholders i.e. policy makers, worker rights organizations, or local NGOs in countries in which its first and lower-tier suppliers operate, as well as actively participating in one or more multi-stakeholder or industry initiatives.
Traceability and Risk Assessment	Supply Chain Transparency	The company demonstrates an understanding of the suppliers and their workers throughout its supply chains by publicly disclosing the names and addresses of its first-tier suppliers, the countries of its below-first-tier suppliers, the sourcing countries of raw materials at high risk of forced labor and human trafficking, and several data points on its suppliers' workforce.
	Risk Assessment	The company has a process to assess forced labor risks, and it publicly discloses forced labor risks identified in different tiers of its supply chains.
Purchasing Practices	Purchasing Practices	The company is taking steps toward responsible raw materials sourcing. It demonstrates through disclosing quantitative data points and providing procurement incentives to first-tier suppliers to encourage or reward good labor practices.
	Supplier Selection	The company assesses risks of forced labor at potential suppliers before entering into any contracts with them, addresses risks related to subcontracting, and discloses details on the outcomes of both processes.
	Integration into Supplier Contracts	The company integrates the ILO core labor standards, which include the elimination of forced labor, into supplier contracts, and requires its suppliers to do the same.
Monitoring	Monitoring Process	The process includes non-scheduled visits, a review of relevant documents, off-site interviews with workers, and visits to associated production facilities and related worker housing. The company also takes steps to ensure suppliers below the first tier are monitored.
	Monitoring Disclosure	The company publicly discloses: the percentage of suppliers monitored annually, the percentage of unannounced monitoring visits, the number or percentage of workers interviewed, information on the qualification of the monitoring organization used, and a summary of findings, including details regarding any violations revealed

Table 5 The table includes four broad indicators of tolerance which include the organizational perspective. The official definition and categorisation of parameter has been obtained from the methodology used by KnowTheChain to benchmark the companies

Indicator	Parameters	Definition
Recruitment	Recruitment Approach	The company has a policy that requires direct employment in its supply chains.The company discloses information on the recruitment agencies used by its suppliers and that the agencies in its supply chains respect the ILO core labor standards.
	Recruitment Fees	The company requires that no worker in its supply chains should pay for a job—the costs of recruitment (i.e., recruitment fees and related costs) should be borne not by the worker but by the employer.
	Monitoring and Responsible Recruitment	The company takes steps to ensure the employment and/or recruitment agencies used in its supply chains are monitored to assess and address risks of forced labor and human trafficking.
	Rights of Workers in Vulnerable Conditions	The company takes steps to ensure the workers understand the terms and conditions of their recruitment and employment and also understand their rights. It further takes steps to ensure its suppliers refrain from restricting workers' movement, and it provides evidence of how it works with suppliers to ensure the rights are respected.
Worker Voice	Worker Engagement	The company works with relevant stakeholders to engage with and educate workers in its supply chains on their labor rights and/or supports worker-led efforts on labor rights education
	Freedom of Association	To support collective worker empowerment, the company works with local or global trade unions to support freedom of association in its supply chains. Where there are regulatory constraints on freedom of association, the company ensures workplace environments in which workers are able to pursue alternative forms of organizing.
	Grievance Mechanism	The company takes steps to ensure a formal mechanism to report a grievance to an impartial entity regarding labor conditions in the company's supply chains is available to its suppliers' workers and their legitimate representatives.
Remedy	Corrective Action Plans	The company's corrective action plans include potential actions taken in case of non-compliance, a means to verify remediation and potential consequences if corrective actions are not taken.
	Remedy Programs	The company has a process to provide remedy to workers in its supply chains in cases of forced labor and human trafficking.

Table 6 The table includes three broad indicators of tolerance which include the employee perspective. The official definition and categorisation of parameter has been obtained from the methodology used by KnowTheChain to benchmark the companies

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