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A SIMULATION-BASED METHOD FOR ANALYZING SUPPLY CHAIN VULNERABILITY UNDER PANDEMIC: A SPECIAL FOCUS ON THE COVID-19

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ABSTRACT

This paper develops a simulation-based quantitative method to investigate the joint impact of multiple risks on the supply chain system during the pandemic. A hybrid simulation method that combines the susceptible-infected-recovered (SIR) model and the agent-based simulation method is proposed to simulate the risk propagation along the supply chain and the interactions between distribution centers and retailers. By analyzing the results of scenarios with different interventions under COVID-19, results show that the impact of interventions is diminishing along the supply chain. For intervention deployment, adding testing capacity is of great importance. For stakeholder management strategies, diversifying the upstream partners is helpful. Against the backdrop of a multi-wave global pandemic, this paper takes the COVID-19 pandemic as an example to provide a paradigm for modeling the risk propagation in supply chain systems. Also, the study demonstrates how to estimate possible time-varying risk scenarios in face of the data shortage challenge.

1 INTRODUCTION

It's been three years since COVID-19 was declared a global pandemic. Almost all countries in the world struggled, and some still are struggling, with this novel coronavirus and the recovery from it. The number of total confirmed cases has exceeded 685 million as of April 2023. The consequences of the pandemic have been far beyond the spread of the virus itself: remote working, extensive business closures, international lockdown, and so on. According to the International Monetary Fund (2022) report, the global economy growth is expected to drop from 6.0 percent in 2021 to 2.7 percent in 2023. COVID-19 has been a stark reminder of the importance of preparedness, cooperation, and resilience in the face of public health crises. The supply chain system, which involves diverse global parties and intricate relationships, is particularly vulnerable. As we look back at the outbreak timeline and how COVID-19 has affected business and society, it is obvious that at the very beginning of the pandemic when many things were unknown and rapidly changing, supply chain systems were under unprecedented chaos. According to a survey that included over 600 companies in the supply chain industry, in the early stage of the outbreak, nearly 60% of respondents reported worsened lead time but the proportion who have a plan to address the disruption is less than 55% (Institute for Supply Management 2020). It's hard to fight back quickly when struck by an unknown pandemic so abruptly and so severe. The knock-on effects of COVID-19 on supply chain are enormous, including product shortage, panic buying, and more. Thus, it's of great importance to study how supply chain systems are affected by the pandemic in the early stage of the outbreak, providing lessons and insights for better preparedness in the future.

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The impact of COVID-19 on the supply chain has attracted a lot of studies and commentaries since its outbreak. The vast majority of the studies are qualitative analyses and discussions from short news releases, interviews of experts, and research papers. For example, McKinsey & Company (2020) provided a group of insights about how stakeholders reset from coronavirus. Rizou et al. (2020) identified possible food safety and environmental safety problems and gave some advice on the detection of the virus in the food supply chain. Quantitative methods including game-theoretical modeling, simulation, and optimization are used to analyze the pandemic topic in the supply chain system. Since Lather and Eldabi (2020) highlighted the importance of using simulation in analyzing the pandemic, researchers have conducted a number of studies. Gupta et al. (2021) studied the pricing decisions under disruptions and gave an optimal pricing strategy considering the disruption timing and product substitution. Ivanov (2020) conducted simulation experiments under different disruption scenarios including disruption only in the supplier and producer, and disruptions in both upstream and transportation sectors. Zheng et al. (2022) did similar simulation experiments but for the medical mask supply chain. The different epidemic duration was used to indicate the supply chain disruptions. Singh et al. (2021) simulated a food supply chain with a facility shutdown scenario and used a backup facility scenario during the pandemic. They highlighted the importance of improving supply chain resilience. Inoue et al. (2023) carried out an agent-based simulation model to explore the economic effects of the lockdown policy. Rozhkov et al. (2022) studied preparedness and recovery policy in supply chain systems with different structures by using an agent-based model. Several excellent review works summarized COVID-19-related work in the supply chain discipline (Chowdhury et al. 2021; Spieske and Birkel 2021; Kohl et al. 2022). They all stressed the value of investigating the impact of COVID-19 on supply chain, not only to combat this pandemic and facilitate recovery, but also to gain readiness for potential future global crises.

As stated above, previous studies mostly focused on the impact of disruptions that occurred at a certain time point, such as simulating the impact of a factory or a producer closure event. These studies ignored the characteristics of the risks brought by the pandemic: the impacts of the risks are time-varying and highly related to the interventions under the pandemic.

Thus, this paper aims to investigate the joint impact of multiple time-varying risks on the supply chain system during the early months of pandemic, when the situation changes rapidly and countermeasures are not yet fully underway. A quantitative simulation-based methodology for the supply chain risk analysis is developed. We dive into the segment from distribution centers to retailers in the supply chain for daily necessities (such as food, drug, and cleaning products) where more people are directly involved. By identifying possible risks in the supply chain and the risk characteristics, this paper estimates the time-varying risk occurrence probabilities when deploying different interventions (quarantine orders, additional testing, vaccine rollout, etc.), and further mimics the propagation of multiple risks from distributors to retailers. After comparing the output performance metrics of different entities, this paper can identify vulnerable entities and give management suggestions on enhancing the anti-risk capacity. Moreover, the comparisons between scenarios with different interventions and disease assumptions are expected to provide us with a clear view of the benefits brought by different policy deployment schemes in the crisis. Although motivated by COVID-19, the method proposed in this paper is generic and applicable to studying the impact of possible epidemic events characterized by temporal variation and widespread outbreaks.

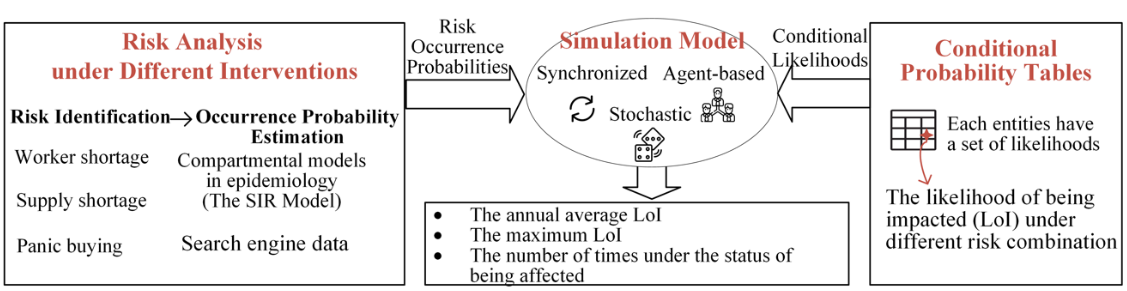


Figure 1: Framework of the proposed simulation-based method.

The framework of our work is shown in Figure 1. Based on the framework, the remainder of this paper is organized as follows. Section 2 presents the risk identification and estimation. Section 3 describes the simulation model. Results and analysis are provided in Section 4. Section 5 concludes the work.

2 RISK IDENTIFICATION AND ESTIMATION

Risks are emerging in both the external environment and every inner link of the supply chain. Hobbs (2020) discussed possible risks under this pandemic from two perspectives: the supply side and the demand side. Based on his work, we further identified three representative risks under this pandemic. On the supply side, we consider an integrated supply shortage (SS) threat, which is a consequence of multiple upstream disruptions. The SS directly hits distributors. Then, defective distributors impact downstream retailers. On the demand side, retailers are stricken by panic buying. Panic buying (PB) threat is the most significant event on the demand side under the pandemic, and has been highlighted in many publications (Hobbs 2020; Zheng et al. 2021). Additionally, worker shortage threats are considered on both the supply side and demand-side, since it's a common problem for all stakeholders in the supply chain.

2.1 Risk Identification

WS is identified as one of the biggest things that impact the whole supply chain. Stephens et al. (2020) pointed out WS problem is especially serious in the food industry since lots of sectors are labor-intensive. Interventions, quarantine restrictions, and sick workers will all lead to a loss of the workforce. Tyson Foods plant in Iowa reported that 60% of employees are infected. All the data tells the same story: both distribution centers and retailers suffer a severe labor shortage problem during this pandemic (Fordham 2020).

SS is another spotlight in the global pandemic. It is a consequence caused by multiple risk events in the upstream supply chain. Transportation disruption, supplier shutdown, export bans, and delivery delays will all lead to SS. Take the Vietnam rice export ban as an example: As the third-largest exporter of rice, the rice export ban raises panic over rice supplies as the virus threat spreads (Nguyen 2020).

The panic buying issue is the response from consumers to the market in the face of a crisis. Consumers stockpile commodities to mitigate possible shortages. Zheng et al. (2021) highlighted the impact of social learning on consumers' behavior. Sales revenue data in Germany shows that the sales revenue of bread mix in the 16th calendar week of 2020 is 61.5% higher than that last year (Evgeniya 2020). Considering that, the panic buying issues in retailers must be studied when conducting the risk analysis.

2.2 Risk Occurrence Probability Estimation

The occurrence probability estimation is an important basis for risk analysis. An occurrence probability indicates the likelihood that a certain risk could occur. In this section, we present how we deal with the lack of data challenge in the pandemic, capture the different risks' characteristics.

The occurrences of WS and SS are highly related to the outbreak condition in the local and surrounding areas. Sick workers cannot be on duty which further leads to WS. We use the number of infected cases to estimate the occurrence probabilities of SS (ζ_t^{SS}) and WS (ζ_t^{WS}) at time t. As shown in Equation (1), the occurrence probability of WS equals the number of infected individuals divided by the population:

$$\zeta_t^{\mathrm{WS}} = \frac{\varphi(t)}{N} \tag{1}$$

where ζ_t^{WS} is the occurrence probability of WS at time t. The time units are in days. The first day of the year has a value $t = 1$. N is the population. $\varphi(\cdot)$ is the empirical distribution of infected cases with time in the study area based on the susceptible-infected-recovered (SIR) model.

SIR model is introduced by Kermack and McKendrick (1927). It assigns the population into three compartments: susceptible, infectious, and recovered, and controls the flow process with parameters, such as transition rates, recovery rate, and time. In this paper, an open and online SIR simulation model for

COVID-19 developed by Eckert and Higgins (2020) is adopted. Figure 2 displays the main interface of the SIR model. When running the model, a time-related curve of the number of infected cases can be obtained.

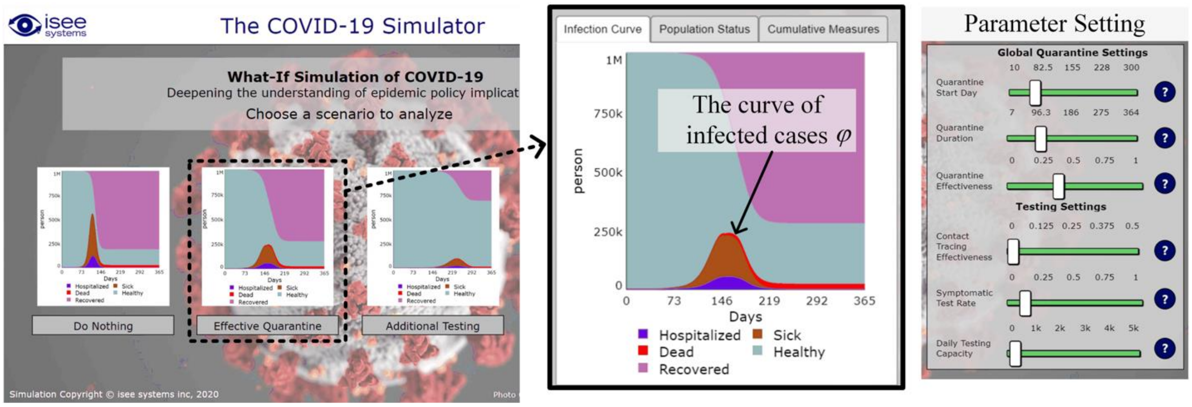


Figure 2: The SIR model for COVID-19 developed by Eckert and Higgins (2020).

In most areas of the U.S. or Europe, SS occurs before WS. While in China, WS occurs first. The rationale behind this assumption is based on the outbreak timeline. The virus outbreak first impacted supplier and producer countries such as China, then relatively late in the other area. That is to say, for most areas in the U.S. or Europe, the occurrence probability curve of the SS is the curve of the WS with a parallel displacement. For example, if the scale of parallel displacement is 15 days, then ζ_t^{SS} is the occurrence probability of SS at time t:

$$\zeta_t^{\mathrm{SS}} = \zeta_{t+15}^{\mathrm{WS}} = \frac{\varphi(t+15)}{N}. \tag{2}$$

Unlike WS and SS risks, PB is a result of global social learning and mostly occur in the very beginning of the pandemic. News portals and social media can easily spark panic around the world via the internet. Thus, we use the search interest data from Google Trends to estimate the PB occurrence probability. Data in Google Trends (2020) are relative numbers between 0 to 100. A higher search interest indicates more search queries have been conducted. The search interest trends of ‘panic buying’ in the U.S. and the U.K., two major English-speaking countries, are very similar. The curves began to increase sharply at the end of February and peaked on March 15, 2020. Though the pandemic outbreak timelines and interventions are different in these two countries, the highly connected internet spreads the fears of stockout and drives global panic buying behaviors almost simultaneously. The search interest has a very small vibration from April to July of 2020, thus we assume the search interests after July equals the average value of the search interests from April to July. As shown in Equation (3), ζ_t^{PB} is the occurrence probability of panic buying of day t:

$$\zeta_t^{\mathrm{PB}} = \begin{cases} \dfrac{\psi(\mathrm{t})}{100}, & t \leq 181 \\ \dfrac{\frac{1}{181}\sum_1^{181}\psi(\mathrm{t})}{100}, & t > 181 \end{cases} \tag{3}$$

where ψ is the empirical distribution of the search interest of the U.S. from Google Trends with time. The bound of the t is 181 since June 30 is the 181st day of this year.

3 SIMULATION MODEL

To further investigate the performance of the stakeholders under risks, a synchronous agent-based simulation model is built. Synchronous modeling indicates that the model status will be updated based on a fixed time step. Figure 3 shows the structure of the simulation model. Every stakeholder (a distribution center or a retailer) is an independent agent with different attributes in the model. Agents can communicate with others through message channels. The communications between different nodes veritably simulate the interactions among stakeholders in the supply chain. For each node, there are two statuses: normal working status and the status of being affected. The status of being affected means the entity is not in full operation.

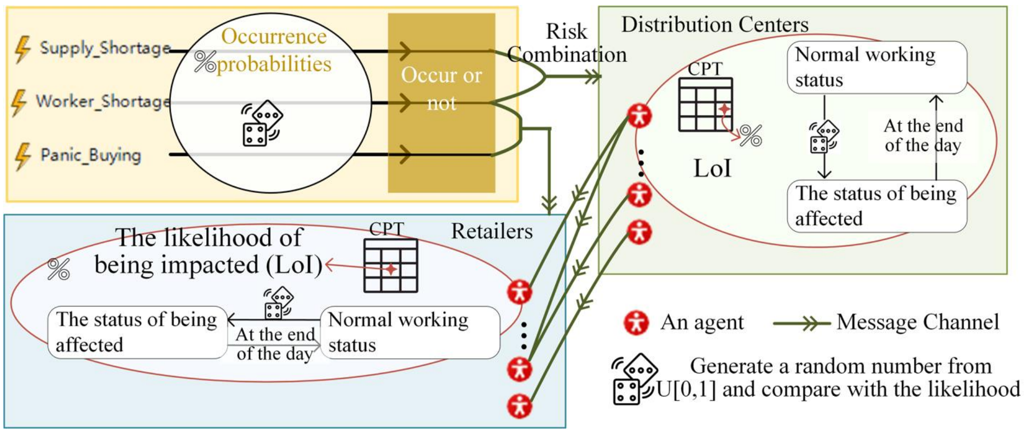


Figure 3: The structure of proposed agent-based simulation model.

The inputs of the simulation model are risk occurrence probabilities and the entities' likelihoods of being impacted (LoIs). LoI is a type of occurrence probability that indicates the probability of transiting to the down status. These probabilities are functions of time and reflect the trend of a random event. To model the randomness, we use random numbers in the risk event trigger processes and status transition event trigger processes, as shown in Figure 4. The green curve shows time-varying the occurrence probability of event m, which reflects the real trend of event m. $f_m(t)$ is a function of time t. At time t_1, the occurrence probability of event m is $l_{m,t_1} = f_m(t_1)$. We denote the random number from the uniform distribution U(0,1) at the time t_1 as α_{t_1}. If α_{t_1} falls into the area below the probability curve ($\alpha_{t_1} \leq l_{m,t1}$), for example α_{t_1} is at point A, then the event will be triggered. If α_{t_1} falls into the orange area above the curve (($\alpha_{t_1} > l_{m,t1}$)), for example α_{t_1} is at point B, then the event will not be triggered.

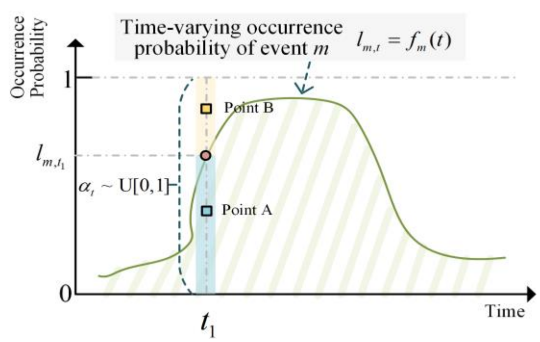


Figure 4: The illustration of randomness modeling based on the empirical distribution.

Every single day, risk events will be randomly triggered according to their occurrence probabilities. Next, a risk combination will be generated. At the same time, every distribution center node will receive the combination message and extract the corresponding LoI from its conditional probability tables (CPT). Based on the LoI, the distribution center node may transit to the status of being affected. After the status transition of distribution center nodes, distribution center nodes will send messages to related retailers. Message-sending channels from a distribution center only send messages to retailers that have business contacts with this distribution center. One retailer may receive messages from several distribution centers. Messages received by retailers include the status of distribution centers and a risk combination. After integrating all messages, retailers will extract the corresponding LoIs from CPTs based on the risk combination and the status of upstream distribution centers, then step into branch blocks. Similarly, retailers will randomly transit to the status of being affected based on the extracted LoIs. The outputs of the simulation model include everyday $l_{m,t}$ of every distribution center and retailer. Based on the $l_{m,t}$ outputs, two metrics are calculated for further analysis: the annual average LoI (denoted as $\bar{l}_m$) and the maximum LoI (denoted as l_m^{MAX}):

$$\bar{l}_m = \frac{1}{T}\sum_{t=1}^{T} l_{m,t} \tag{4}$$

$$l_m^{\mathrm{MAX}} = \max\left(l_{m,1}, l_{m,2}, l_{m,3}, \dots, l_{m,t}\right) \tag{5}$$

where T is the total number of days in the simulation period. The annual average LoI calculated in Equation (4) indicates the average likelihood of being impacted. The maximum LoI calculated by Equation (5) is the peak value for the whole year.

The third performance metric (denoted as K_m) is defined to be the number of times that entity node m is being affected:

$$K_m = \sum_{t=1}^{T} \mathbf{1}_{(l_{m,t},1]}\left(\alpha_{m,t}\right) \tag{6}$$

where $\mathbf{1}_{(l_{m,t},1)}\left(\alpha_{m,t}\right)$ is an indicator function that yields 1 if $u_{m,t} \in \left(l_{m,t}, 1\right)$ and 0 otherwise. If the generated random number $\alpha_{m,t}$ falls in range $\left(l_{m,t}, 1\right)$, $\alpha_{m,t}$ is greater than the likelihood of occurrence $l_{m,t}$, hence the node m is being affected at time t.

4 CASE STUDY

A case study is conducted based on a case city in the state of New Jersey, the most densely populated state in the US. Experiments are developed for a supply chain network case with 13 nodes which include 6 distribution centers and 7 retailers of different economic scales (small, medium, and large), as shown in Figure 5. The proportion of small, medium, and large enterprises is based on the statistics data of the study area from the United States Department of Agriculture (USDA). We further divided distribution centers into three supply diversity levels: high diversity level, medium diversity level, and low diversity level. Four scenarios with different interventions are considered. Based on the real data of the case area, the parameters in the SIR model in different scenarios are listed in Table 1:

Table 1: Parameters for baseline scenarios in the SIR model based on New Jersey.

Parameter	Do Nothing (D. N)	Effective Quarantine (Eff. Quar)	Additional Testing (Add. Test)	50% Vaccination Coverage (Vacc.Cov50%)
Quarantine Start Day	80	80	80	80
Quarantine Duration (days)	0	77	77	77
Quarantine Effectiveness	0.1	0.37	0.1	0.1
Daily Testing Capacity	0	0	2.5k	0
Contact Tracing Effectiveness	0	0	0.5	0
Symptomatic Test Rate	0.1	0.1	0.25	0.1
Infectivity	0.4	0.4	0.4	0.26

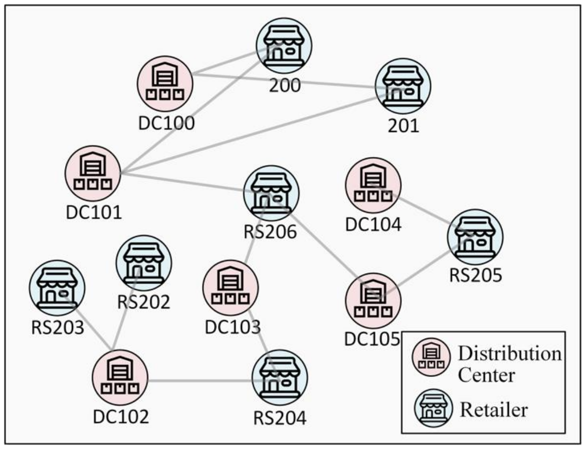


Figure 5: The 13-node supply chain network in our study.

Figure 6 presents the time-varying occurrence probabilities of the three risks under four scenarios. The panic buying issues first sweep across the city. The outbreak of the virus then leads to a supply shortage issue. Subsequently, the community-level spread extends into the study area, and the worker shortage problem occurs. The occurrence probabilities will be the inputs of the next-step simulation.

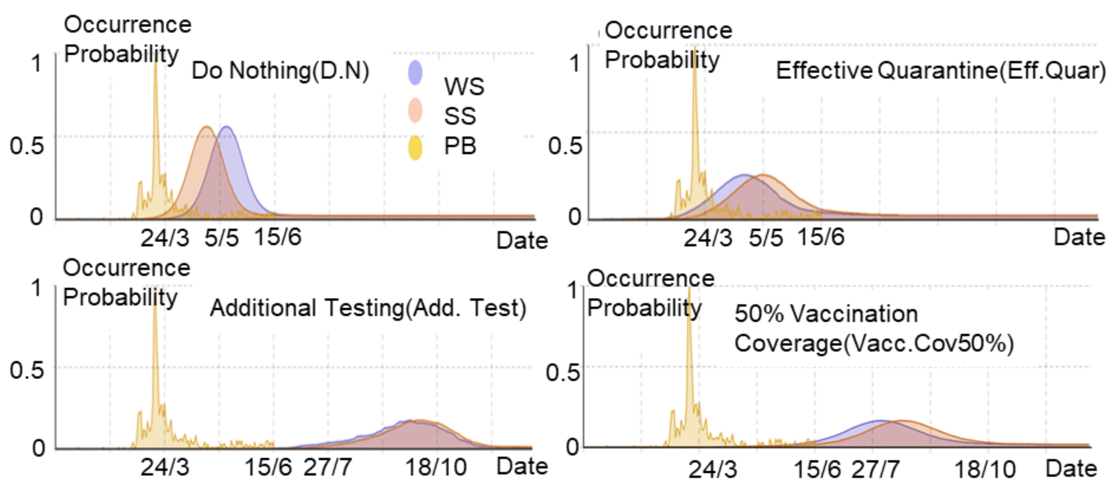


Figure 6: The illustration of randomness modeling based on the empirical distribution.

The CPTs are generated based on the following assumptions:

1. Small enterprises (distribution centers and retailers) are more susceptible to worker shortage since they may not have enough staff reserves;
2. Small enterprises (distribution centers and retailers) are more susceptible to worker shortage since they may not have enough staff reserves;
3. Distribution centers with a low diversity level are more susceptible to supply shortage given risk diversification;
4. Small retailers are more susceptible to panic buying considering the limited stock.

Table 2 lists the CPT for distributors. Table 3 to 8 present the CPTs for retailers. In a CPT, “Y” indicates the occurrence of a corresponding risk event, while “N” indicates nonoccurrence. NFO indicates not in full operation. A risk combination is a scenario with the occurrence of different risk events.

Table 2: The conditional probability table (CPT) for distributors.

Supply Diversity Level	Economic Scale		Risk Combination			
		Supply Shortage	Y		N	
		Worker Shortage	Y	N	Y	N
Low	Large	DC100	0.60	0.50	0.35	0.10
High	Large	DC101	0.55	0.45	0.35	0.10
Medium	Medium	DC102	0.60	0.40	0.40	0.10
High	Medium	DC103	0.65	0.45	0.40	0.10
Medium	Small	DC104	0.70	0.40	0.45	0.10
High	Small	DC105	0.75	0.45	0.45	0.10

Table 3: The conditional probability table (CPT) for retailers 202 and 203.

Economic Scale		Risk Combination							
	DC 102 NFO	Y				N			
	Worker Shortage	Y		N		Y		N	
	Panic Buying	Y	N	Y	N	Y	N	Y	N
Medium	RS202	0.65	0.55	0.55	0.30	0.45	0.35	0.35	0.10
Small	RS203	0.85	0.70	0.65	0.30	0.65	0.50	0.45	0.10

Table 4: The conditional probability table (CPT) for retailers 200 and 201.

Economic Scale		Risk Combination															
	DC100 NFO	Y								N							
	DC101 NFO	Y				N				Y				N			
	WS	Y		N		Y		N		Y		N		Y		N	
	PB	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Large	RS 200	0.45	0.40	0.40	0.20	0.40	0.35	0.35	0.15	0.40	0.35	0.35	0.15	0.35	0.30	0.30	0.10
Medium	RS201	0.65	0.55	0.55	0.30	0.55	0.45	0.45	0.20	0.55	0.45	0.45	0.20	0.45	0.35	0.35	0.10

Table 5: The conditional probability table (CPT) for retailer 204.

Economic Scale		Risk Combination															
	DC102 NFO	Y								N							
	DC103 NFO	Y				N				Y				N			
	WS	Y		N		Y		N		Y		N		Y		N	
	PB	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Small	RS204	0.85	0.70	0.65	0.30	0.75	0.60	0.55	0.20	0.75	0.60	0.55	0.20	0.65	0.50	0.45	0.10

Table 6: The conditional probability table (CPT) for retailer 205.

Economic Scale		Risk Combination															
	DC104 NFO	Y								N							
	DC105 NFO	Y				N				Y				N			
	WS	Y		N		Y		N		Y		N		Y		N	
	PB	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Small	RS205	0.85	0.70	0.65	0.30	0.75	0.60	0.55	0.20	0.75	0.60	0.55	0.20	0.65	0.50	0.45	0.10

Table 7: The conditional probability table (CPT) for retailer 206 Part I.

Economic Scale		Risk Combination															
	DC101 NFO	Y															
	DC103 NFO	Y								N							
	DC105 NFO	Y				N				Y				N			
	WS	Y		N		Y		N		Y		N		Y		N	
	PB	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Small	RS206	0.85	0.70	0.65	0.30	0.75	0.60	0.55	0.20	0.75	0.60	0.55	0.20	0.70	0.55	0.50	0.15

Table 8: The conditional probability table (CPT) for retailer 206 Part II.

Economic Scale		Risk Combination															
	DC101 NFO	N															
	DC103 NFO	Y								N							
	DC105 NFO	Y				N				Y				N			
	WS	Y		N		Y		N		Y		N		Y		N	
	PB	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Small	RS206	0.75	0.60	0.55	0.20	0.70	0.55	0.50	0.15	0.70	0.55	0.50	0.15	0.65	0.50	0.45	0.10

Considering the randomness of the simulation model, the results presented in this section are the average value of 100 runs. Figure 7 shows the annual average LoI of each node under four scenarios. Several conclusions can be obtained from this figure. Firstly, both three interventions (effective quarantine “Eff.Quar”, additional testing “Add.Test” and 50% vaccination coverage “Vacc.Cov50%”) are effective to mitigate the risks. Compared with quarantine only, introducing additional testing capacity can significantly reduce the LoI of all nodes. The effectiveness of Vacc.Cov50% is closed to Add.Test. Then, in all four scenarios, large and medium retailers are less vulnerable than small retailers. The average LoI of the large retailer RS200 is much lower than other retailers. RS201 and RS202 are two medium enterprises with different distributors. Their annual average LoIs are very close. Among the four small retailer enterprises, RS206 is less vulnerable than the other three retailers. RS206 has commercial contacts with three distribution centers, which is the most among all retailers. This phenomenon highlights the importance of risk diversification. In other words, multiplying the supply resources is one of the effective ways to reduce vulnerability. Another noteworthy finding is that the differences among distribution centers are less noticeable compared with that among retailers. It’s a ripple effect along the supply chain. A similar ripple effect has also been noticed in Ivanov et al. (2020).

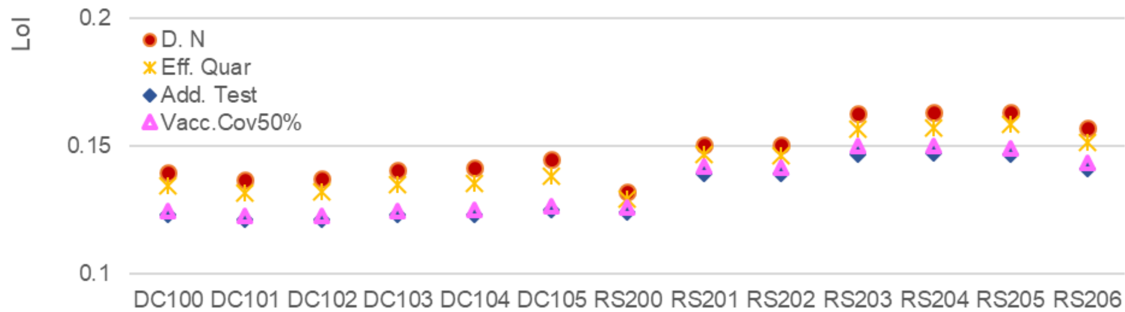


Figure 7: The annual average likelihood of being impacted ($\bar{l}_m$) of each node.

When investigating the maximum LoI in Figure 8, the first thing we notice is that interventions can effectively reduce the maximum LoI of distribution centers but become powerless on reducing the maximum LoI of retailers. For example, the maximum LoI of DC100 decreased more than 40% from the "Do Nothing" (D.N) scenario to the "50% Vaccination Coverage" (Vacc.Cov50%) scenario. However, the decrease of RS200's maximum LoI from scenario D.N to scenario Add.Test is less than 1%. The reason for the results is that these countermeasures don't ease the early panic buying behavior. l_m^{MAX} occurs in the early stage when retailers are still shocked by the panic buying risk. Per the results of average LoIs, small and medium enterprises and retailers with fewer distribution centers have high maximum LoIs which is unfavorable. In Add.Test, the maximum LoI of RS203 is 1.5 times the maximum LoI of RS200.

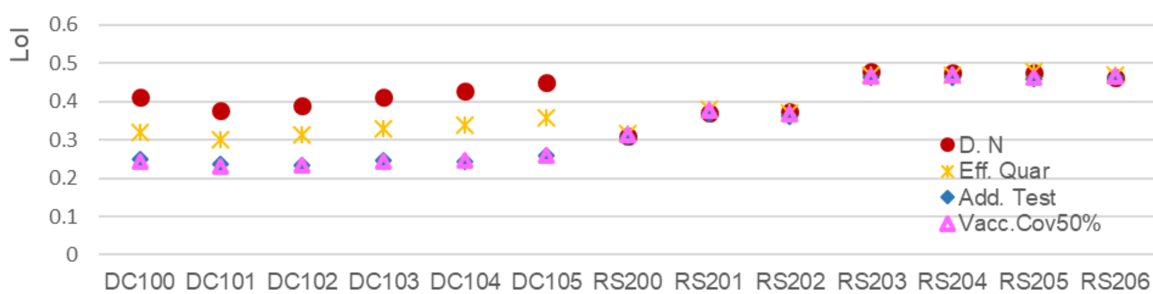
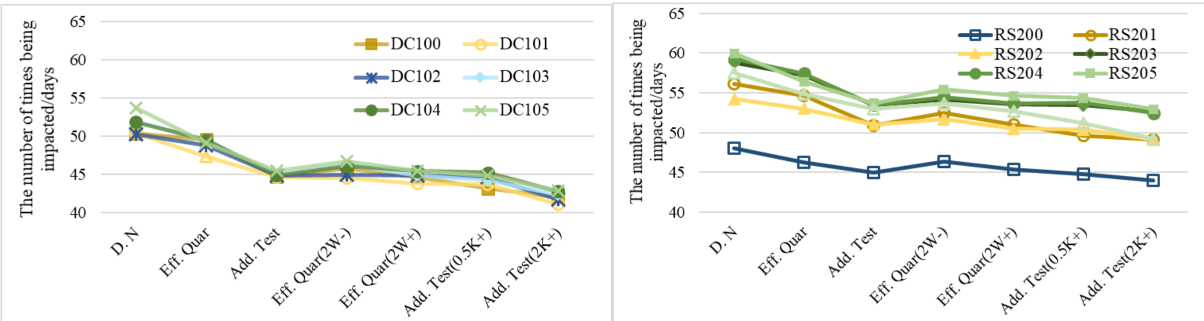


Figure 8: The maximum likelihood of being impacted (l_m^{MAX}) of each node in the baseline scenarios.

Figure 9 presents the number of times the status of being affected (K_m). Apart from the four aforementioned scenarios, four additional scenarios are conducted for further analysis. Firstly, we adjust the quarantine duration to investigate how much the quarantine duration will matter. The Eff.Quar (2W–) and scenario cuts a two-week quarantine duration down, and the Eff.Quar (2W+) scenario adds two more weeks of quarantine. Secondly, two new scenarios are generated to investigate the impact of increasing testing capacity. The Add.Test(0.5K+) scenario has 500 more testing kits per day, while the Add.Test(2K+) scenario has 2,000 more kits per day. Not surprisingly, the effect of cutting down the quarantine duration is negative. It will lead to a slight increase in K_m. The benefits of longer quarantine duration are limited. The biggest difference is found in DC101. The number of times under the status of being affected of DC100 decreased by only 2% from the baseline Eff.Quar to the Eff.Quar (2W+) scenario. In comparison, the benefits brought by additional testing kits are relatively obvious. In the Add.Test(0.5K+), seven nodes have more than 1% decrease in the number of times being affected compared with the baseline Add.Test. When expanding the daily testing capacity with additional 2 thousand kits, the number of times being affected of DC101 decreased 8% from the baseline Add.Test. In short, adding testing capacity can effectively mitigate risks along the supply chain. Moreover, the differences among retailers are more significant than the differences among distribution centers. Big retailer enterprise RS200 outperforms all other retailers.



(a) K_m for distribution centers (b) K_m for retailers

Figure 9: The number of times under the status of being affected (K_m).

5 CONCLUSION AND DISCUSSION

This paper developed a simulation-based methodology to analyze risks brought by COVID-19 in the supply chain and investigate the vulnerability of the entities in the supply chain. Based on the performance metrics of each entity, we analyze the performance of entities in a well-designed supply chain network under different interventions (effective quarantine, additional testing, and vaccine rollout). Results show that the benefits brought by additional testing capacity and vaccine rollout are more obvious than that of effective quarantine. A ripple effect can be observed: differences in performance metrics among retailers are more obvious compared with that among distribution centers.

The main contributions of our work are two-fold: From a scientific perspective, the risk analysis methodology provides a paradigm for linking healthcare data and search engine data to supply chain management to overcome the data shortage challenge. Also, the agent-based simulation model provides a paradigm for modeling the risk propagation between stakeholders in supply chain systems. From a practical perspective, by comparing the performance under different interventions, our work can provide insights for decision-makers on the impact of the interventions, and also advise enterprises on how to strengthen their ability to withstand the disruptions.

Though we have made some progress in estimating and simulating the risk propagation, limitations related to data analytics exist. Regarding future directions, we look forward to further studies on data analytics methodology about extracting useful data for supply chain management from multiple data sources, such as social media, and the healthcare industry. Studies on the disruption of globalization considering different nations' policies are also very important. We also point to models on supply chain reconfiguration.

REFERENCES

Chowdhury, P., S. K. Paul, S. Kaisar, and M. A. Moktadir. 2021. "Covid-19 Pandemic Related Supply Chain Studies: A Systematic Review". *Transportation Research Part E: Logistics and Transportation Review* 148:102271.

Eckert, A. and D. Higgins. 2020. The Covid-19 Simulator: What-If Simulation of Covid-19. isee systems inc., isee systems. https://exchange.iseesystems.com/public/isee/covid-19-simulator/index.html#page1, accessed 6th April.

Evgeniya, K. 2020. Panic Buying During Coronavirus in Germany in 2020: Food Retail Sales Revenue Change. https://www.statista.com/statistics/1104200/coronavirus-panic-buying-food-retail-sales-revenue-change-germany/, accessed 26th May.

Fordham, E. 2020. 60% of Employees Positive for Coronavirus at Iowa Tyson Foods Meat Plant. https://www.foxbusiness.com/markets/coronavirus-cases-tyson-meat-plant-iowa, accessed 6th May.

Google Trends. 2020. Google Trends Related to 'Panic Buying'. https://trends.google.com/trends/explore?date=2020-01-01%202020-07-26&geo=US&q=panic%20buying, accessed 17th April.

Gupta, V., D. Ivanov, and T.-M. Choi. 2021. "Competitive Pricing of Substitute Products under Supply Disruption". *Omega* 101102279.

Hobbs, J. E. 2020. "Food Supply Chains During the Covid‐19 Pandemic". *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 68(2): 171-176.

IMF. 2022. World Economic Outlook Update, World Economic Outlook, October 2022: Countering the Cost-of-Living Crisis, https://www.imf.org/en/Publications/WEO/Issues/2022/10/11/world-economic-outlook-october-2022, accessed 1st April.

Inoue, H., Y. Murase, and Y. Todo. 2023. "Supply-Chain Simulations for Shaping Lockdown Policies". *Spatial Economic Analysis* 18(3):368-386.

Ivanov, D. 2020. "Predicting the Impacts of Epidemic Outbreaks on Global Supply Chains: A Simulation-Based Analysis on the Coronavirus Outbreak (Covid-19/Sars-Cov-2) Case". *Transportation Research Part E: Logistics and Transportation Review* 136:101922.

ISM. 2020. Coronavirus Outbreak in China: Impact to Supply Chain, https://www.ismworld.org/globalassets/pub/research-and-surveys/pdf/docs_coronavirus-outbreak-in-china-impact-to-supply-chain_v3-3.pdf, accessed 5th March 2020.

Kermack, W. O., and A. G. McKendrick. 1927. "A Contribution to the Mathematical Theory of Epidemics". *Proceedings of The Royal Society A: Mathematical, Physical and Engineering Sciences* 115 (1927): 700-721.

Kohl, M., A. Habl, K. Kallali, J. Puff, J. Fottner, R. Oger, M. Lauras, and J. Li. 2022. "Managing Supply Chains During the Covid-19 Crisis: Synthesis of Academic and Practitioner Visions and Recommendations for the Future". *The International Journal of Logistics Management* 33(4): 1386-1047.

Lather, J. I., and T. Eldabi. 2020. "The Benefits of a Hybrid Simulation Hub to Deal with Pandemics". In *2020 Winter Simulation Conference (WSC)*, edited by K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, 992-1003. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

McKinsey & Company. 2020. The Next Normal: How Companies and Leaders Can Reset for Growth Beyond Coronavirus. https://www.mckinsey.com/featured-insights/coronavirus-leading-through-the-crisis, accessed 5th June.

Nguyen, S. 2020. Coronavirus: Vietnam Stockpiles Rice as Outbreak Spreads and Food Security Concerns Grow. https://www.scmp.com/week-asia/economics/article/3077272/coronavirus-vietnam-stockpiles-rice-outbreak-spreads-and-food, accessed 28th March.

Rizou, M., I. M. Galanakis, T. M. S. Aldawoud, and C. M. Galanakis. 2020. "Safety of Foods, Food Supply Chain and Environment within the Covid-19 Pandemic". *Trends in Food Science & Technology* 102:293-299.

Rozhkov, M., D. Ivanov, J. Blackhurst, and A. Nair. 2022. "Adapting Supply Chain Operations in Anticipation of and During the Covid-19 Pandemic". *Omega* 110:102635.

Singh, S., R. Kumar, R. Panchal, and M. K. Tiwari. 2021. "Impact of Covid-19 on Logistics Systems and Disruptions in Food Supply Chain". *International Journal of Production Research* 59(7): 1993-2008.

Spieske, A., and H. Birkel. 2021. "Improving Supply Chain Resilience through Industry 4.0: A Systematic Literature Review under the Impressions of the Covid-19 Pandemic". *Computers & Industrial Engineering* 158:107452.

Stephens, E. C., G. Martin, M. van Wijk, J. Timsina, and V. Snow. 2020. " Impacts of Covid-19 on Agricultural and Food Systems Worldwide and on Progress to the Sustainable Development Goals". *Agricultural Systems* 183:102873.

Zheng, R., B. Shou, and J. Yang. 2021. "Supply Disruption Management under Consumer Panic Buying and Social Learning Effects". *Omega* 101:102238.

Zheng, Y., L. Liu, V. Shi, W. Huang, and J. Liao. 2022. "A Resilience Analysis of a Medical Mask Supply Chain During the Covid-19 Pandemic: A Simulation Modeling Approach". *International Journal of Environmental Research and Public Health* 19(13): 8045.

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