Ten-tier and Multi-scale Supply Chain Network Analysis of Medical Equipment: Random Failure & Intelligent Attack Analysis

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This paper explores supply chain viability through empirical network-level analysis of supplier reachability under various scenarios. Specifically, this study investigates the effect of multi-tier random failures across different scales, as well as intelligent attacks on the global supply chain of medical equipment, an industry whose supply chain's viability was put under a crucial test during the COVID-19 pandemic. The global supply chain data was mined and analyzed from about 45,000 firms with about 115,000 intertwined relationships spanning across 10 tiers of the backward supply chain of medical equipment. This complex supply chain network was analyzed at four scales, namely: firm, country-industry, industry, and country. A notable contribution of this study is the application of a supply chain tier optimization tool to identify the lowest tier of the supply chain that can provide adequate resolution for the study of the supply chain pattern in the medical equipment sector. We also developed data-driven-tools to identify the thresholds for the breakdown and fragmentation of the medical equipment supply chain when faced with random failures, or different intelligent attack scenarios. The novel network analysis tools utilized in the study can be applied to the study of supply chain reachability and viability in other industries.
Keywords: supply chain network, medical equipment, multi-tier, multi-scale, disruption, random failure, intelligent attack, supply chain breakdown

1. Introduction

The global medical equipment supply chain network can be studied through different scales of network structure spanning across multiple tiers. Motivated by COVID-19, we assess the vulnerability of the medical equipment supply chain at the *network-level* (Ivanov and Dolgui, 2021) to various interruptions at the firm, industry, and country scales. The supply chain data on which this study relies consists of 115,118 real relationships between 44,927 firms, with other scales of the network being computed from the firm-scale data. To the best of our knowledge, the previous studies in this area have been conducted either using stochastic, synthetic (simulated) supply chain networks (c.f. Sen et al., 2020; Yang et al. 2021; Wang et al. 2018) or using relatively small local supply chain structures (c.f.; Hernandez and Pedroza-Gutierrez, 2019, research on seafood market in Guadalajara, Mexico based on the study of 10 wholesalers, using a single tier). Considering that "synthetic networks" are constructed using "random network models" to represent a simulation of multi-tier supply chains (Yang et al. 2021) they can provide an opportunity for researchers to practice various scenarios in synthetic supply chain structures, assuming access to information about the supply chain.

Despite the convenience of using simulated networks to study real-world constructs, these simulated networks come with restrictive assumptions and simplifications that limit the implications of the findings. For example, in an innovative study on supply chain resilience and restoration after a crisis using simulation data, Mao et al. (2020), assume that all firms in the supply chain will select the shortest path during restoration, which is not widely applicable to real-world supply chains. Additionally, data scientists using simulated models face various limitations, including credibility, scalability (Rampfl, 2013), reliability, accuracy, different algorithms' characteristics, and generalizability of the findings (Cassens et al. 2005). The alternative to simulated data has traditionally been carefully curated, real-world data. The advantage

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of this approach is that the topology is more realistic than in the random graph models, so the results may be more relevant. However, it is very difficult to collect enough real-world data to capture the multi-tier, multi-scale complexity of global supply chains, so in general, studies using real networks can suffer from serious missing data/boundary effects as well as a lack of understanding of how generalizable the conclusions are to broad industries. In contrast to such previous studies, the present study utilizes a novel data collection method to get a comprehensive picture of the entire real-world global supply chain among public firms.

2. Literature Review

Several contemporary events, including cyber-attacks, terrorism, and more recently, the COVID-19 pandemic, have highlighted the fragility of the global supply chains. Researchers and policymakers have called for development of new solutions for designing and managing global supply chains that are better responsive to “the risk of disruption” (c.f. Sherkarian et al. 2020). The organizational supply chain's ability to manage the disruptions is of particular importance “in the time of crisis” for critical supplies such as medical equipment (Okeagu et al., 2021). Okeagu et al. (2021), in their study on the effect of COVID-19 in the U.S. medical system, call for better “transparency of where our raw materials are sourced, diversifying of our product resources, and improving our technology.” While companies do not voluntarily report their supply chain information, there are opportunities for data scientists to mine and analyze such data from the available data sources to explore the vulnerability of global supply chains to disruptions. “Disruptions are unexpected events occurring in a supply chain” (Wu et al., 2007) and are closely related to risk and uncertainties in the supply chain (Blackhurst and Wu, 2009). The supply chain’s abilities to manage uncertainties and disruptions has been widely studied using various metrics, including agility, robustness, vulnerability, flexibility, and adaptability, to name a few. Each metric corresponds to the supply chain’s ability to prevent disruption and/or recover from a disruption (Zegordi and Davarzani, 2012). Appendix 1 displays the definition of these abilities.

Supply chain abilities can enable the organization to continue operations despite various uncertainties and disruptions, be they short-term, long-term, minor, or significant. The COVID-19 “pandemic is characterized by a rapid spread” that affected not only supply and demand but also global logistics (Grida et al., 2020). The short-term effect of COVID-19 interruption has been observed in the daily life of society as well as in critical medical operations (Okeagu et al., 2021). Various export bans of medical equipment that went into effect in 2020 are examples of “protectionism in the pharmaceutical and medical supplies sectors” that put considerable short-term pressure on global supply chains (Stellinger, Berglund, and Isakson, 2020, pp: 23). In the long-term, businesses are expected to adapt to new patterns of production and trade, which stem from operational necessities as well as protectionist policies. “Dismantling the international supply chains, [and] reliance on domestic production” (Yacoub, and El-Zomor, 2020, pp:11) is a real possibility as a result of policies defined by “medical protectionism,” and “retreat from global supply chains” (Baldwin and Evenett, 2020, pp: viii) is expected.

This study employs a network view of the global supply chain within the General Systems Theory. Network analysis is “an essential tool for studying system resilience” due to its capability “to capture relationships and dependencies between components” (Williams and Musolesi, 2016). Advances in data mining and big data computation, along with recent developments in “analysis of...spatial and temporal network[s],” have provided researchers with tools to conduct “more accurate” analysis of many real-world network systems (Williams and Musolesi, 2016). Supply chain optimization practices (Haque, Paul, Sarker, and Essam, 2020) and globalization of markets and productions have made the global supply chains less centralized (Abele, Elzenheimer, Liebeck, Meyer, 2006; Mourtzis D., Doukas 2006). Advanced network models have proven capable of analyzing complex networks “even in completely decentralized architectures” (Trajanovski, Scellato, and Leontiadis, 2012).

Mathematicians have widely used spatio-temporal systems analysis in a variety of fields for identifying weaknesses across connected networks; including social networks (Trajanovski, Scellato and Leontiadis, 2012), transportation networks (Williams and Musolesi, 2016), and traffic flows (Shi, Yue, Zhou, 2019) just to name a few. Since the focus of this study is on a static global supply chain, we do not utilize a dynamic network analysis that tracks changes using a time variable. Such dynamic longitudinal studies can be a subject of future studies. As the supply chain of medical equipment has implications in the nations' quality of life and national security, previous studies on infrastructure and military supply resiliency (c.f. Brown et al. 2005, Barrow 2019) have contributed to the better understanding of critical supply chains. Brown et al. (2005) argue that while commercial supply chains may not be generally considered as critical infrastructure, "they are certainly critical" to the "well-being" of a nation. Disturbances to the networked infrastructure may be caused by "random failure, deliberate attacks, and natural disasters" (Wang et al., 2013). In this research, we simulate both the random failures (caused by unexpected events, e.g. *inter alia* natural disasters or a container ship gets stuck in Suez Canal) and the intelligent (targeted) attacks on the global supply chain of the medical equipment (e.g. *inter alia* terrorist attack, trade war/dispute, technological platform attack, or sanction) to explore how such ruptures can affect the critical medical supply firms. Considering the complex and intertwined nature of the global supply chains, such analysis needs to be conducted across all notable tiers and units of analysis (scales) of the global supply chain. In this study, we will discuss how multiscale network data can be analyzed across different tiers of the supply chain to assess the reachability of suppliers in case of disruption.

3. Research Methodology

In their well-cited paper on supply chain disruption, Wu et al. (2007) discuss the intertwined global supply chain of products and services. Network-based modeling and analysis have been a recommended "methodology for supply chain distortion analysis" that addresses the complex, multi-tier, nonlinear, global, and dynamic characteristics of organizational supply chains (Wu et al. 2007). In arguably one of the most targeted and comprehensive investigations in the supply chain literature about "disruption propagation and structural dynamics," Ivanov and Dolgui (2021) argue that this area has been explored using three categories of methodological tools, namely, network and complexity theory, mathematical optimization, and simulation studies. The present work can be best classified a network and complexity theory where supply chain analysis is conducted on the "macro view of the supply chain structure" and "operational parameters" are not the subject of the research (Ivanov and Dolgui, 2021).

In the following, some of the network-based methods to study supply chain disruptions are discussed along with their application in the present study. The research methodology is influenced by the research goal as well as the characteristics of data. We discuss how our network disruption analysis methodology incorporates previous research methods to be compatible with our data's structure.The application of Petri-nets has been discussed in the literature as a method for analyzing disruption risk and uncertainly in complex global supply chain networks. The Petri-net mathematical modeling language is useful to understand how a disruption can be disseminated throughout the supply chain and affect operational performance (Zegordi and Davarzani, 2012). While previous works are conducted to understand supply chain disruptions on the basis of the risk probability, the Petri-net modeling does not require the availability of such probability distributions, which are usually constructed based on past experiences (Zegordi and Davarzani, 2012). This characteristic of Petri-net modeling is a supporting argument for the use of Petri nets, and similar network analysis approaches in exploring supply chain disruptions for events for which we do not have probability estimates, such as the COVID-19 pandemic. Petri-net models have been utilized by firms with access to detailed product information, including the bill of materials and production process of their products/service. While such information is not available at the global supply chain scale, we adopt the "reachability" analysis approach used in Petri-net modeling across the network (Wu et al. 2007, Zegordi and Davarzani, 2012; Fierro and Garcia, 2020). "Reachability" is the basis of our supply chain disruption analysis. In this paper, we explore how the firms' access (or reach) to their multi-tier supply chain is affected when an interruption or a series of interruptions occurs across the global supply chain of medical equipment.

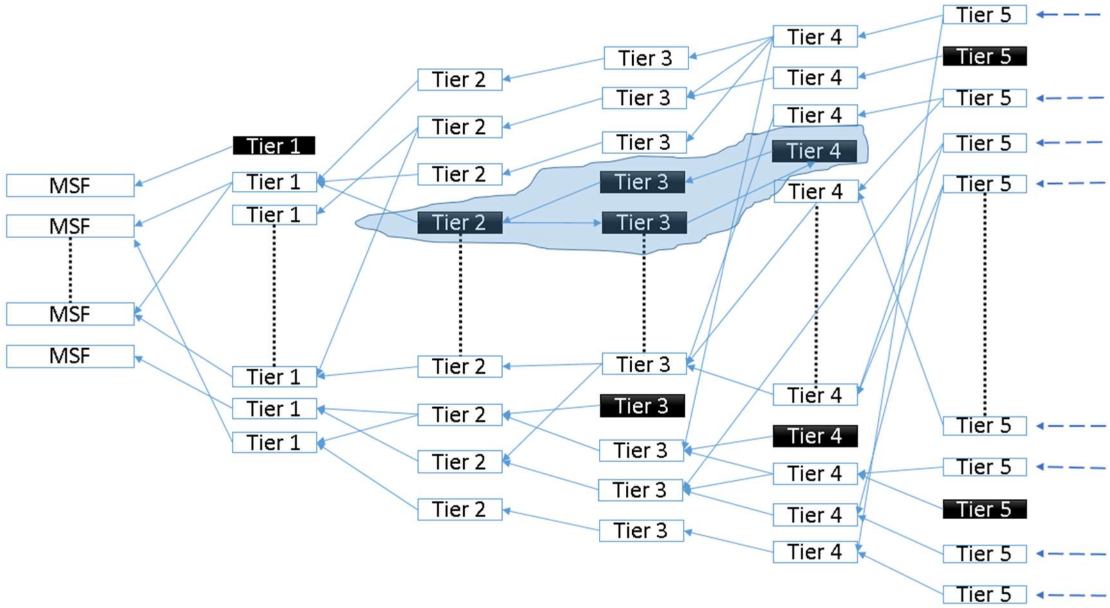
Sauer and Seuring (2019), in their study on multi-tier supply chain reach, propose a cascaded approach. Supply chain cascading analysis has been widely used to analyze disruptions in the context of computer network architecture (c.f. Potts et al. 2020), computer network security (c.f. Yan et al., 2014), infrastructure networks such as power-grids (c.f. Ash and Newth, 2007; Guo et al., 2019), and traffic networks (c.f. Li et al. 2019). Cascading failure in these studies is usually caused by the overload of the network, which is not frequently applied to supply chain failure analysis. In a recent study, Yang et al. (2021) utilized the cascade failure method to study supply chain robustness. They argue that "when a node is disrupted, its downstream and upstream neighbors will be affected due to supply shortage and demand losses, respectively." From this perspective, both underload and overload can negatively affect the supply chain robustness through not only inventory but also the cost (Sun et al. 2020). For example, in the case of an underload, the supply chain may be disrupted due to unfavorable economies of scale in backward or forward tiers of the supply chain. In general, the disruptions to the supply chain can be intelligent (or targeted) attacks or random failures (Sun et al. 2020). Therefore to explore the vulnerability of the supply chains to disruptions, researchers should explore random failures as well as intelligent disruptions that may occur using scenario simulations. In our research methodology, we will conduct both random failure analysis and intelligent attacks analysis.

In this study, following the previous outline of scholarly research, we utilize reachability analysis similar to the Petri-net models and conduct failure analysis across multiple tiers of the supply chain as described in cascading failure models. There have been limited previous studies using the supply chain reachability method to the best of our knowledge, and no research has been conducted using such methodologies on real-world, large-scale supply chain data. The limited number of previous studies that utilized similar methods have explored other aspects of the supply chain, such as supply chain sustainability analysis in small scales or using stochastic methods (c.f. Kumar and Rahman, 2017; Bommel, 2010). In this study, the global supply chain reachability will be conducted in the presence of random failure and intelligent attacks using real-world supply chain data. In the following, we discuss our approach in conducting intelligent attacks and random failure analyses across multiple tiers and scales of the global supply chain of medical equipment.

4. Data Collection

While scholars have called for transparency with regards to supply chains of critical products and services such as medical equipment (Okeagu et al. 2021), companies do not voluntarily publish such information because it is of strategic importance to their competitiveness. However, according to the Securities and Exchange Commission (SEC) and Statement of Financial Accounting Standards (SFAS), publicly traded firms are mandated to report their notable customers and suppliers, among other information. Item 101 (17 CFR 229.101) of the SEC requires firms to report their business description. As a part of item 101 and SFAS No. 131 requirements, corporations registered with SEC are required to disclose information about the suppliers and customers that "accounted for 10 percent or more of consolidated" revenue/cost "in any of the last three fiscal years, or if total revenue did not exceed $50,000,000 during any of those three fiscal years, 15 percent or more of consolidated revenue" or cost (SEC, 33-7620). We refer to these firms as "notable" customers and suppliers. This legal requirement provides data scientists an opportunity to gain access to notable global supply chain data. To the best of our knowledge, this is the most comprehensive large-scale feasibly and legally available supply chain data. The supply chain data for this research is prepared and provided by the XXX Data Science Lab[2]. A schematic map of the first 5 tiers of this data is presented in Figure 1.

Figure 1. Network Data Structure: Tier-by-Tier Data Collection.



MSF: Medical Supply Firms (MSF). *Blacked out nodes are Terminal Suppliers (TS)* *Shaded area represents a loop.*

As a simplification, Figure 1 presents each tier as disjoint. In reality, our supply chain network is nonlinear, and many firms are present across multiple tiers. Medical Supply Firms (MSF) which are wholesale and distributors of medical equipment, are the starting point of data collection. Terminal Supplier (TS) are firms in the supply chain for which we don't know of any higher-tier dependencies, and they are identified in Figure 1 by blacked-out nodes. These TSs are not necessarily in the last tier, as lower-tier firms are not guaranteed to report any notable suppliers in higher tiers, or there may be firms that are active in more than one tier. The supply chain network includes numerous cycles and self-loops. An example of a supply chain loop is presented in Figure 1, where the shaded area identifies the supply chain loop members. In the case of the supply chain loops that include a TS, all members of the loops are identified as TSs due to their supply chain dependencies. In the analysis section, we have provided the analytical justification for our choice to collect ten tiers of data.

The data collection's starting point is all of companies listed in the SNL Financial, S&P Capital I.Q., and Compustat under the Standard Industry Classification (SIC) 5047, which was 324 firms at the time of data collection. SIC-5047 represents companies in the Medical, Dental, and Hospital Equipment and Supplies sector. The information about notable suppliers of 267 MSF firms was available to be mined. Ten rounds of data mining and preparation were performed to construct the 10-tier supply chain network. The network was constructed from 115,118 real relationships between 44,927 firms. We could not identify the primary industry identification for close to one third of the firms. To address this issue, industry classifications were randomly assigned to the missing data based on the proportion of representation of each industry in the sample, with this random assignment being re-done in each repeated experiment to

2 a member of the XXX Data Science Lab is a co-author, to protect the anonymity of the review process, the name of the Lab will be provided after the review process

understand any possible variation in outcomes. Appendix 2 illustrates the distribution of the suppliers as well as the number of new firms we mined at each round of data collection. The data was initially collected at the firm-scale. Using the firm-scale data, we constructed the same supply chain network at the industry scale, country scale, and country-industry scale. The industry-scale and country-scale supply chain networks are self-explanatory. To generate the country-industry supply chain network, we differentiated each firm's industry by the country where it's headquarters is located, following Lavassani's (2017) proposed multi-scale network analysis approach.

5. Data Analysis

As disruptions may occur at the firm scale, country scale, country-industry scale, or industry scale, it is imperative that businesses and policymakers have the capability to understand and analyze disruptions at all scales. As described in the data collection section, we have constructed the supply chain networks at four scales (firm, industry, country-industry, and country) across ten tiers. The multi-scale analysis approach is employed to provide the opportunity to analyze disruptions that can happen at different scales. For example, consider global sanctions placed on a particular industry in a specific country; in this case, the country-industry-scale would be a suitable analysis scale.

Before conducting disruption experiments caused by random and intelligent events, we utilize a tier count optimization tool to identify the most efficient supply chain network depth to analyze. This supply chain depth optimization tool has notable application in the validity analysis of supply chain network data collection and efficiency of future studies. Our data collection optimization tool is based on the application of ideas from mathematical analysis and convergence theory, which are widely applied throughout the simulation sciences, particularly mathematical physics. (c.f., Scott 2011, chs 12-13 for introductory material.)

In this study we utilize different random failure and intelligent attack methodologies which are commonly used to study complex networks in the fields of mathematics physics, and system resiliency (c.f. Liu et al. 2005; Magnien et al. 2011; Yamashita et al., 2019; Sičanica and Vujaklija, 2020). To analyze the effect of disruptions, we conducted Random Failure Experiments (RFE) and Intelligent Attack Experiments (IAE) of the global supply chain across different tiers and scales. The RFEs and employee-based IAEs are performed using 100 realizations. Due to missing industry categorization for some firms, we also repeat the industry-level PageRank-based experiments 24 times, each with a different imputation of the missing industry values, drawn with replacement from the distribution of industries that are known. We also plot the percentile intervals of valuations from random and randomized attacks, from the 2.5th percentile to the 97.5th percentile. The results are further discussed in the following section.

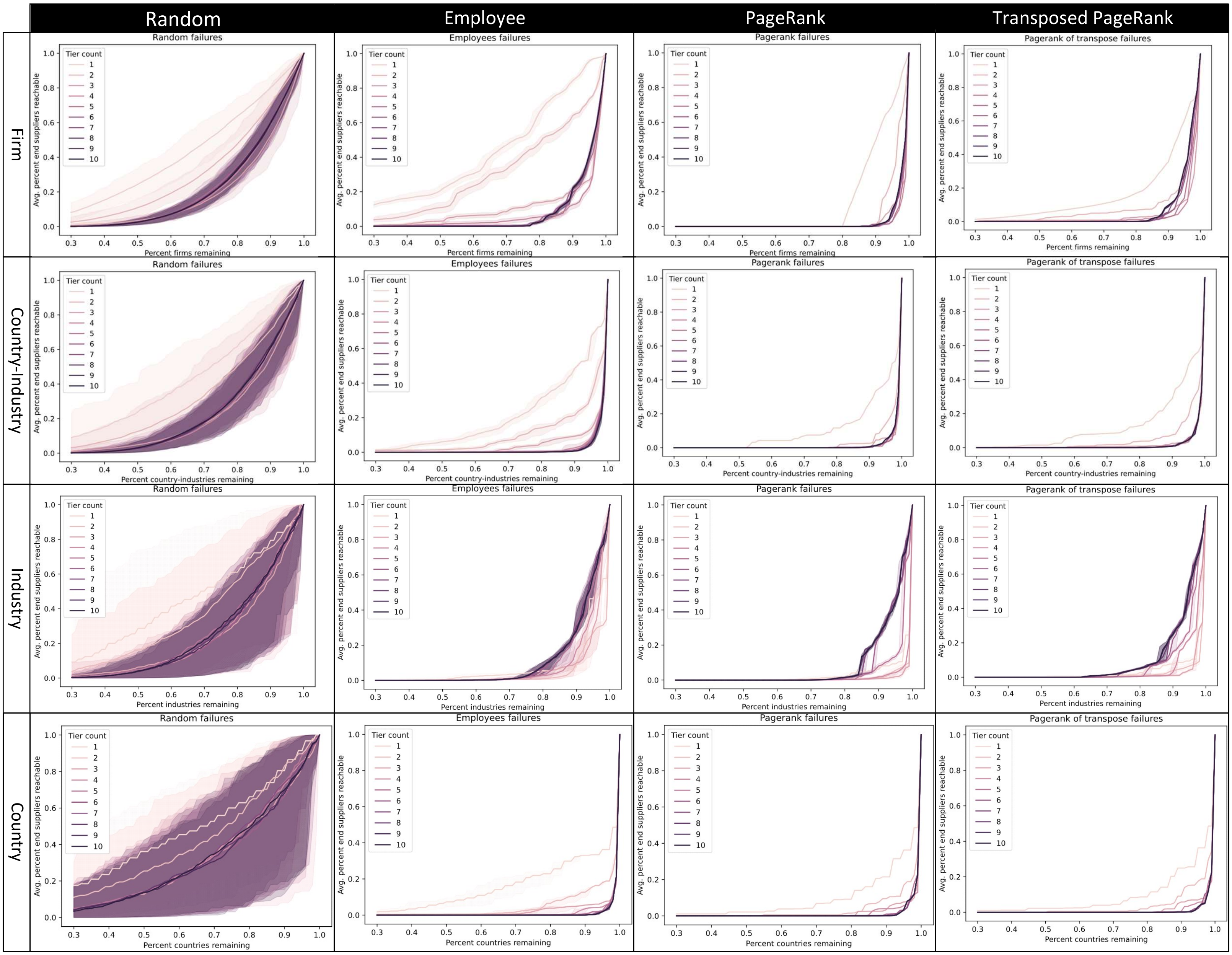
For conducting the IAE, we need to define target attack criteria. The centrality of network actors is a natural selection in the context of the network analysis. We selected PageRank centrality with respect to the network and its transpose as reasonable proxies for importance with respect to upstream and downstream firms, respectively. That is, under PageRank with/without transpose, the most central firms are those most relied on by their suppliers/customers, respectively. We looked for other available moderating factors that could affect firms' influence in the supply chain network. We could collect the number of employees for 95% of firms in our supply chain network. In the absence of edge weights, the number of employees is a meaningful measure of a firm's size and influence in the supply chain network. Centrality and the number of employees are used as criteria to launch IAEs. To measure the consequence of RFA and IAE on the global supply chain, we measured the average percentage of TSs Reachable (ATSR) as well as whether at least one TS was reachable (Some Terminal Suppliers Reachable, or STSR), averaged across MSFs.

Centralities are calculated at the firm-scale. The centralities at other scales were calculated based on the aggregation of centralities of the firm-scale. The location of the firms are identified by their country of headquarter. Industries are classified based on each firm's primary SIC code. Disruption investigations are conducted using the above-mentioned classification. For example, when we remove an industry on the basis of RFA or IAE, all firms classified within that SIC code get eliminated from the supply chain network. Finally, we present two data-driven approaches to identify the threshold of disruption that may lead to breakdown and fragmentation of the global supply chain for medical equipment. The data analysis is presented in six subsections, namely, supply chain tier, firm scale, industry scale, country-industry scale, country scale and supply chain breakdown and fragmentation.

5.1 Supply Chain Tiers Analysis

The decision about selecting the number of tiers is data-driven. The supply chain data is collected tier by tier, and due to the nature of the supply chain network, the data can be collected virtually across an unlimited number of tiers. However, due to the large size of the data and computational limitations, a data scientist should identify the optimal number of tiers that best represent the structure of the global supply chain pattern. This issue is crucial since as we expand data collection from one tier to the next, the number of firms in each supply chain tier may grow exponentially. This exponential growth is expected to slow down at some point as there is a finite number of firms. Our analysis across different scales provides mathematical evidence for the appropriate number of tiers that can best represent the supply chain pattern for each type of analysis (i.e., random failures vs. intelligent attacks) and each scale of analysis (e.g., firm- vs. country-scale). Figure 2 displays the result of RFA and IAE across the four scales of analysis. IAEs are conducted based on firms size (employee count), PageRank, and transposed PageRank.

Figure 2. RFA & IAE Across Multiple Tiers of Supply Chain.



X: One minus the Supply Chain Failure Rate (SCFR)
Y: Average Percent of Terminal Suppliers Reachable (ATSR)
In the random/randomized failure analysis: Realizations= 24-100.
Shading represents the range from the bottom 2.5th percentile to the top 97.5th percentile interval over realizations.

The Y-axes in Figure 2 represent the average percentage of the end suppliers which are reachable (where the average is taken across MSFs); this statistic is equal to one minus Supply Chain Failure Rate (SCFR). The X-axes indicate the percent of remaining operating firms, representing the percentage of firms that are still in business under the RFE and IAE.

Our analysis demonstrates that the SCFRs across different tiers in the medical equipment industry have high correlations. The shaded areas capture 95% of the data spread across random realizations of firm failure order and/or industry/employee count imputation where needed. Such imputations were made by drawing randomly from the distribution of employee counts and industries which were known. This shaded area shows the range of probable disruption variation when the supply chain experiences random failure. Each of the RFEs or IAEs in Figure 2 displays where the network reaches convergence. To have a reasonably appropriate estimation of the supply chain structure, researchers need to collect data from appropriate number of tiers of supply chain. To identify the tier in which the network converges we use uniform convergence of the mean as a function of percent firms remaining. We subtracted the mean ATSR curve with 10 tiers from the one with fewer tiers and take the absolute value. The largest value of the resulting function is then the uniform distance. Starting with one tier and adding tiers until the uniform distance is small enough (5% in our tests) we identified how many tiers are needed for convergence. Based on the analysis of each disruption across different scales of supply chain, we recommend a minimum number of supply chain tiers to be analyzed for each disruption scenario as displayed in Table 1.

Table 1. Disruption scenarios and minimum recommended supply chain tiers to be analyzed.

Failure/Attack mode / Unit	RFA	IAE		
	Random	PageRank of transpose	PageRank	Employee
Firm	4	8	7	6
Country-Industry	3	5	6	4
Industry	5	8	8	7
Country	4	4	7	6

According to our analysis, for the purpose of RFA analysis at the firm-scale, we need to collect data from at least four supply chain tiers. In this scenario, the supply chain's reachability pattern stabilizes after the 4^{th} tier; we call this the convergence tier count. Including higher tiers of the supply chain in this scenario marginally enhances the network's resolution of the supply chain pattern. Another example we discuss here is the IAE based on employee count at the firm-scale; in this scenario, six tiers provide evidence that required supply chain information is collected to have a converged supply chain pattern for further research.

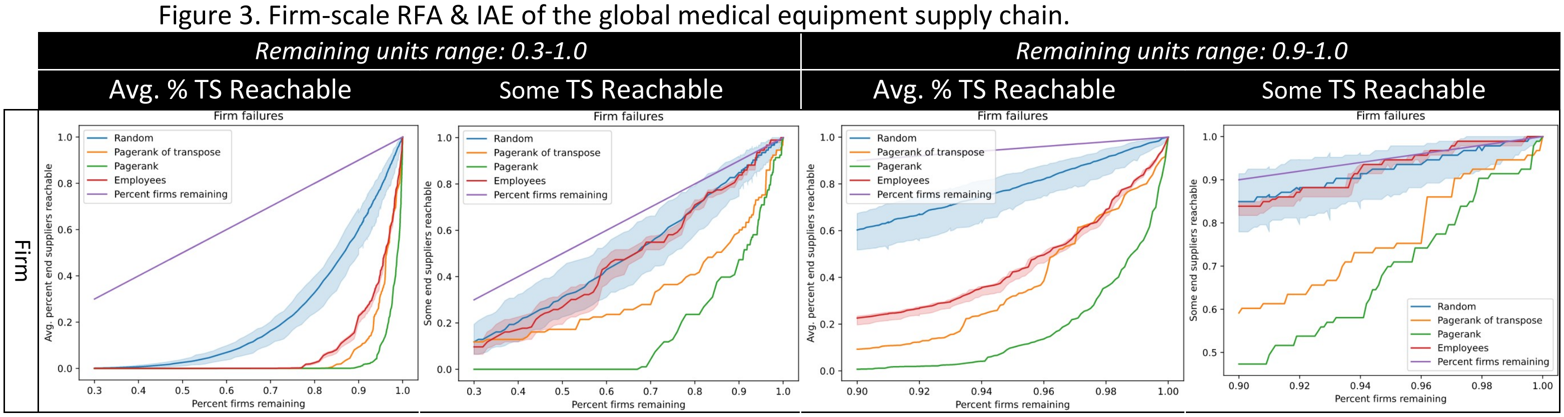
In addition to the findings about the recommended number of tiers that need to be analyzed, we also identified several interesting patterns of supply chain disruptions. One of the interesting observations is related to the case of industry-scale PageRank IAE. In this case, we recommend using at least eight tiers to obtain the best supply chain failure pattern depending on the scale of attack. Six to seven tiers in this scenario would be sufficient for attacks that take out up to approximately 10% of industries; however, for attacks that affect more than the 10% threshold, our analysis suggests collecting data from at least eight tiers. Based on the pattern of failure at this scale of analysis (Figure 2), it is expected that should data be collected from higher tiers, the supply chain may show more robustness and continue to show a stepped-down pattern of catastrophic failure when the percentage of 'firms remaining' continues to decrease beyond 0.8. In other words, an analysis with fewer tiers may overemphasize how fragile the supply chain is to this type of targeted attack. Another interesting finding based on the analysis of the pattern of supply chain disruptions across different tiers can be observed in the result of RFA at the country scale and the industry scale. The dark shaded areas representing the bottom 2.5^{th} percentile shown below the mean reachability curves display the possibility of a catastrophic disruption with a relatively small elimination of units. For example, a 5% disruption at the industry-scale or at the country-scale can potentially cause 80% of MSFs TSs to become unreachable.

If we consider 20% reachability of TSs from MSFs as a “catastrophic” supply chain failure, we expect this threshold would not be reached unless at least 30% of industries or countries are eliminated from the global supply chain of medical equipment. However, our IAE analyses indicate that should a few (appx. 5%) of the notable industries or countries be eliminated from network, we can reach a catastrophic supply chain failure at a much earlier stage. The RFA analysis at the industry scale and the country scale reveals another interesting characteristic. In RFA at the industry scale and country scale, as we collect and analyze supply chain data from higher tiers, the likelihood of higher TSs’ reachability (shaded area above the curves) decreases, however, the likelihood of catastrophic failure (shaded area under the curves) does not decreases notably. We started by conducting our analysis using 5 tiers and gradually increased our data collection to 10 tiers. At the 10th tier, we had supportive evidence that the data is collected from appropriate tiers of the supply chain to conduct more detailed analyses at different scales. We will discuss these analyses in the following sections.

5.2 Firm-scale Supply Chain: RFA and IAE Analysis

Figure 3 displays the RFA and IAE analysis of the global supply chain of medical equipment at the firm-scale. The RFA is conducted using 24 realization and visualized with a shaded area encompassing 95% of the observed values of Average percent of TSs reachable (ATSR). To better focus on the data ranges where notable changes occur, the analysis is presented at 0.3-1.0 and 0.9-1.0 remaining firms ranges. We have plotted the ATSR and the percent of MSFs with Some TSs being reachable (STSR) when the supply chain is faced with random failure or various intelligent attacks. Conducing analysis using ATSR and STSR provides further insight for business strategists. In scenarios where interruptions are short term, MSFs have buffer inventory for some inputs (e.g. parts), there exist substitute inputs, and/or MSFs can source some inputs from other suppliers, the STSR can be a better measure of MSFs’ supply chain operability. ATSR arguably could be a better benchmark for assessing the MSFs’ supply chain operability in scenarios where these conditions do not apply.

Figure 3. Firm-scale RFA & IAE of the global medical equipment supply chain.



The results indicate the effectiveness of each form of disruption on the global supply chain. Overall we have supportive evidences that the most effective disruption can be caused by an intelligent attack which is based on the centrality of the firms in global supply chain. Intelligent attacks targeting lower-tier central suppliers (PageRank) is found to be more effective in disrupting supply chains than targeting higher-tier central suppliers (PageRank of the transposed network). Also, random failures are found to be the least effective in disrupting the supply chain. Finally, intelligent attacks based on firm's size (as measured by the number of employees) are found to have a similar effect as a random failure on STSR.

It is noteworthy to mention that the distance between the percentage of firms remaining (purple line) and various failure/attack scenarios is attributed to the network effect stemming from supply chain dependencies. We can observe when and to what extend these dependencies affect ATSR and STSR. For example in the STSR graphs (Figure 3) we can observe that the network effects of random failure and intelligent attacks are modest in the >95% firms remaining range; however, failures that affect more that 10% of firms will cause notably larger disruptions. In the case of ATSR the network effects of disruptions are larger and earlier.

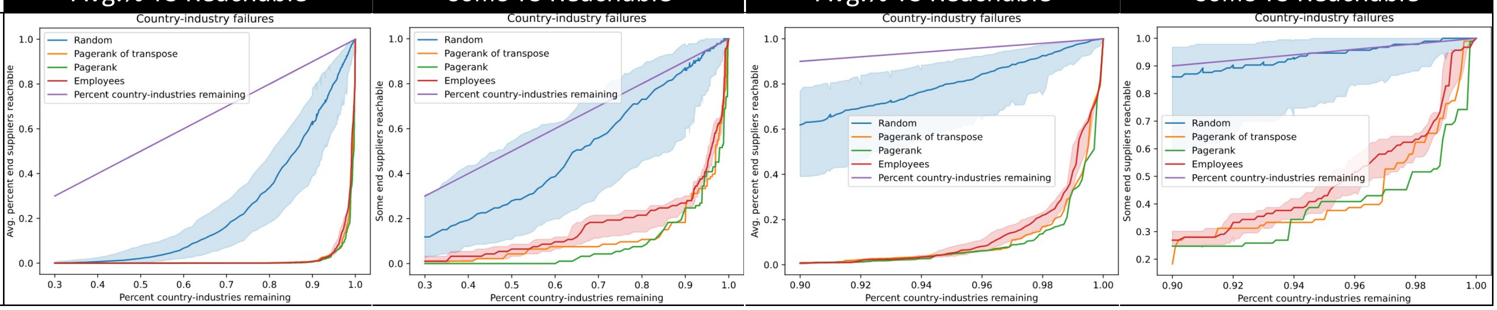
5.3 Country-Industry-scale Supply Chain: RFA and IAE Analysis

Figure 4 presents the analyses at the country-industry scale. In the ATSR analyses, different intelligent attack methods produce very similar scales of disruptions even it the 0.9-1.0 range. Similarities can be observed in STSR analyses as well; however, the PageRank-based attacks and transposed PageRank attacks are marginally more effective than size-based attacks.

Figure 4. Country-Industry-scale RFA & IAE of the global medical equipment supply chain.

	Remaining units range: 0.3-1.0		*Remaining units range: 0.9-1.0*	
	Avg.% TS Reachable	Some TS Reachable	Avg.% TS Reachable	Some TS Reachable

Country-Industry

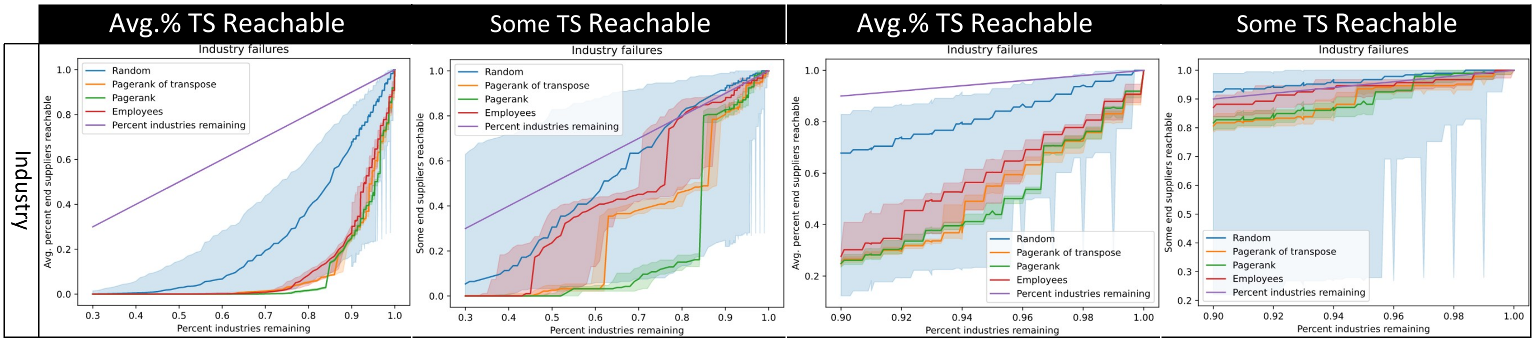


5.4 Industry-scale Supply Chain: RFA and IAE Analysis

The industry-scale analysis measures the impact of random or targeted elimination of an industry. The two centrality-based attacks almost produce identical effects on ATSR and STSR. This implies that attacks targeting higher influential tiers or lower inferential tiers at the industry-scale are expected to result in the same scale of interruptions. It is notable to mention that the supply chain shows notable resiliency in centrality-based industry attacks under STSR scenarios within a certain attack range. Specifically, we can expect over 80% of TSs to stay reachable when approximately 15% of the industries are eliminated. In this scenario, the random attack has a reasonable probability of causing more devastating supply chain disruption as identified by the shaded area reaching below intelligent attack curves (at certain ranges of remaining industries).

Figure 5. Industry-scale RFA & IAE of the global medical equipment supply chain.

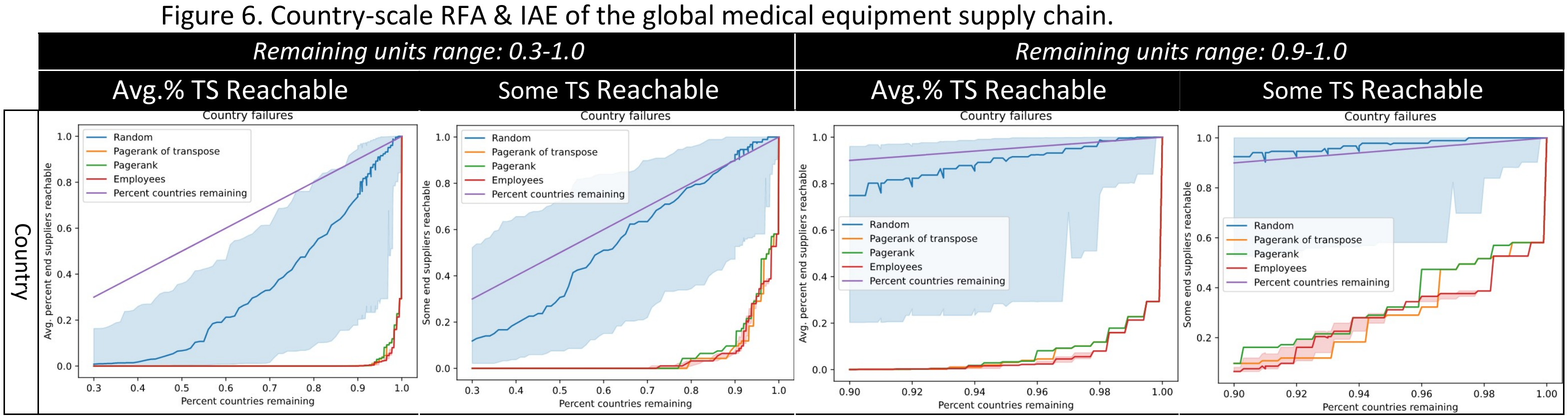
Remaining units range: 0.3-1.0	*Remaining units range: 0.9-1.0*



5.5. Country-scale Supply Chain: RFA and IAE Analysis

Our analysis across different scales reveals that as we move from firm-scale and country-industry-scale analysis to industry-scale and country-scale analysis, the variability of interruption resulting from random failures increases. This issue can be observed by comparing the shaded areas between the 97.5 and 2.5 percentile of outcomes. According to this, the firm-scale analysis result has the lowest uncertainty. Figure 6 displays the result of the analyses conducted at the country scale.

Figure 6. Country-scale RFA & IAE of the global medical equipment supply chain.



Our analysis shows the important role of some major countries like the U.S., China, and a few other countries whose elimination can create significant disruption to the global supply chain. This issue can be observed in the IAEs of all scenarios in Figure 6. When the first major country is eliminated based on any of the IAEs, we can observe that the reachability of intelligent attacks starts to drop to approximately 25% for ATSR and 60% for STSR.

5.6. Supply Chain Breakdown and Fragmentation.

Another interesting finding of this study is with regards to the threshold of global supply chain breakdown or fragmentation at different scales. To the best of our knowledge and as reported in the literature (c.f. Wang et al. 2018) “there is no threshold” that can determine what scale of interruption will result in the complete breakdown of global supply chain operations.

Supply Chain Breakdown

Based on our global medical equipment models, the breakdown thresholds can be estimated from RFA and IAE results (Figures 3, 4, 5 and 6). Table 2 summarizes the thresholds based on the supply chain breakdown where the "breakdown threshold" is defined here as the largest value of percent firms remaining at which ATSR was less than 20% or 1%. Depending on the researchers' needs other limits may be utilized using the same methodology. (Lee et al., 2019, Rapisardi et al., 2018).

Table 2. Supply chain breakdown threshold of global medical equipment.

Failure/Attack Type	Scale	Supply Chain Breakdown Threshold: 20% limit remaining	20% limit affected	1% limit remaining	1% limit affected
Random	Firm	0.73	0.27	0.42	0.58
	Country-industry	0.72	0.28	0.41	0.59
	Industry	0.71	0.29	0.38	0.62
	Country	0.60	0.40	0.29	0.71
PageRank of transpose	Firm	0.934	0.0766	0.84	0.16
	Country-industry	0.983	0.017	0.91	0.094
	Industry	0.88	0.12	0.66	0.34
	Country	0.988	0.012	0.94	0.063
PageRank	Firm	0.967	0.033	0.91	0.095
	Country-industry	0.987	0.013	0.90	0.096
	Industry	0.88	0.12	0.76	0.24
	Country	0.988	0.012	0.94	0.063
Employees	Firm	0.89	0.11	0.77	0.23
	Country-industry	0.978	0.022	0.92	0.084
	Industry	0.87	0.13	0.70	0.3
	Country	0.988	0.012	0.94	0.063

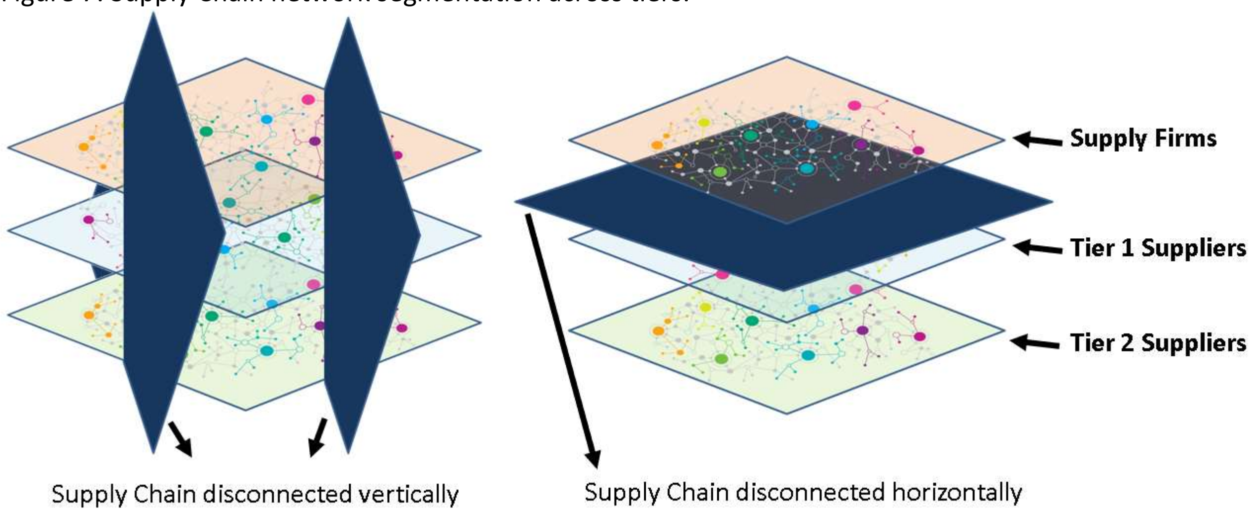
As illustrated in Table 2, the supply chain breakdown thresholds are dependent on the type of disruption, scale of analysis, and desired breakdown limit values (here calculated based on 20% limit and 1% limit). For example when only 27% of the firms are affected by a random failure, the ATSR of the global supply chain for MSFs falls down to 20%. If the breakdown limit is defined at the 1% limit, the breakdown can be achieved when 58% of firms are randomly affected.

Overall the intelligent attacks are found to be notably more efficient in achieving supply chain breakdown limits. For example a country-industry PageRank-based attack can achieve the supply chain breakdown limit of 20% by targeting merely 1.3% of country-industries, while achieving the same level of supply damage through random failure calls for 28% of country-industries to be eliminated from the global supply chain. The comparison of PageRank and PageRank of transpose also provides interesting results. The attacks at the more macro-scales (industry-scale and country-scale) have the same level of efficiency in both types of attacks. However, PageRank is found to be marginally more effective in attacks at the firm and country-industry-scale. While PageRank provides more weight on the importance of lower tier suppliers, from the perspective of PageRank of transpose, higher tier suppliers are viewed to be more important. According to this result eliminating lower tier suppliers is more efficient in achieving supply chain breakdown limits than eliminating higher-tier suppliers. While this result applied to the sample of medical equipment global supply chains, in other industries the supply chain breakdown thresholds may exhibit different patterns.In the absence of a threshold that can determine the breakdown of supply chains we provided a solution to identify thresholds based on the defined breakdown limits. These limits can be determined by scholars and practitioners considering their needs.

Supply Chain Fragmentation

In addition to the above mentioned methods we also introduce and utilize a fragmentation threshold identification methodology from the field of graph theory based on the Erdős–Rényi (ER) model (Erdős and Rényi, 1959). The reachability statistics used in this paper are tailored to the case of supply chains, but they do bear a superficial similarity to more classical "network robustness" analyses that have roots in percolation theory (c.f. Bunde and Havlin 1996). In such analyses, undirected graphs are generally assumed to have been drawn from a random graph model, and the goal is to determine, in the limit of infinitely large graphs, what proportion of nodes must be removed either randomly or in a targeted manner, in order to break up the graph into many connected components. Classical percolation theory does not apply to undirected graphs, nor is our preceding analysis meant to imply anything about whether the supply chain consists of multiple connected components. To visualize the difference, we imagine the supply chain laid out in tiers, with each tier occupying a single layer (See Figure 7).

Figure 7. Supply Chain network segmentation across tiers.



If we cut (disconnect) the supply chain horizontally, all our reachability statistics are zero, but the network only contains two giant components. Conversely, if the chain is sliced vertically several times, our reachability statistics can be quite high, even though the supply chain is broken into many pieces. Indeed, the vertical slicing does correspond to competing business ecosystems which supply among themselves but not with each other, which is a feature of modern supply chains. Nonetheless, due to the prominence of percolation theoretical approaches to network robustness, it is interesting to compare our results with what might be obtained using more classical tools. We limit ourselves to the four most popular analyses: Erdos-Renyi (ER, uniformly random) vs. power law graphs and random vs. (degree) targeted attacks. Note that random and targeted attacks are approximately equally effective for ER graphs.

In graph theory, the network robustness is measured by assessing "the impact of node failure on the integrity of a network" (Barabási , 1999). This method is widely utilized in statistical physics and mathematics within the context of percolation theory (c.f. Bunde and Havlin 1996 , Zheng et al. 2021). Based on percolation theory principals we explore the change in the structure of the network when nodes or edges are removed from the network. We start removing the supply chain nodes until the average degree of each node is less than 1 (corresponding to the ER robustness limit). We use the ER's connectedness threshold to identify the critical threshold of network fragmentation. In this study we refer to this network fragmentation as *supply chain fragmentation*. The result of this analysis is presented in Table 3COLAP.

Table 3. Supply chain fragmentation threshold of global medical equipment.

		Supply Chain Fragmentation Threshold	
	Scale	Avg. node degree <1	
		Remaining	**Affected**
Random failure	Firm	0.21	0.79
	Country-industry	0.19	0.81
	Industry	0.02	0.98
	Country	0.01	0.99

We define the supply chain fragmentation as the situation where the supply chain network is broken into disconnected components, identified by the average degree falling below 1. Albert, Jeong, and Barabasi (2000), in their work "Error and attack tolerance of complex networks" explain that for ER networks, targeted and random failures are about equally effective at fragmenting the network. The result from Table 3 shows that the robustness of the supply chain network measured using the ER model varies across different scales. The primary reason for this behavior is that, as we move our scale from firm and country-industry and from industry and country the random failures will have lower probability of eliminating highly central nodes. The supply chain of medical equipment includes a relatively small number of extremely well connected nodes and hence exhibits a highly skewed degree distribution. This characteristic makes this supply chain particularly robust to various types of disruptions.

In the case of power law networks, we use the Molly-Reed criterion and an estimate of 1.4 for the power law exponent (obtained using the powerlaw python package). Thus, for random attacks all but .8% of firms must be deleted in order to break up the network. In the targeted case, the theory predicts that arbitrarily small attacks should break up the network. This is broadly consistent with the extreme observed efficacy of targeted attacks on the real network, which is expected, since the actual degree distribution is quite heavy-tailed.

6. Discussion

Ivanov and Dolgui (2020), as some of the seminal scholars in the field, promoted the study of viability analysis based on the intertwined network of supply chains. Ivanov and Dolgui (2020) highlighted the different behaviors of intertwined supply chain networks versus the traditional linear supply chains. As we identified in the complex network of about 150,000 supply chain connections, there exist numerous supply chain loops. As we expanded mining supply chain data tier by tier, we also identified numerous lower tier suppliers become suppliers to the higher tier firms. These firms create intertwined value co-creation business ecosystems forming what Dolgui, Ivanov and Sokolov (2020) refer to as "value webs".

Overall, the global supply chain network of medical equipment exhibits high vulnerability exhibited by a sharp decrease in TSs reachable to MSFs when the supply chain is faced with disruptions. The high scale of vulnerability is due to the very few alternative routes from higher-tier suppliers to the MSFs. The reason for such a vulnerable network structure is twofold. On the one hand, the medical equipment supply chain requires incorporating a high scale of service (Maltz and Maltz, 1998) due to its final products' complexity and sensitive nature. This factor limits the flexibility of MSFs to maintain costly supplier relationships with multiple suppliers simultaneously. On the other hand, over the past few decades, efficiency goals (NASEM, 2018; Jha, 2019) have "forced" (Denton and Jaska 2014) MSFs to adopt creative efficiency practices and strategies including "pull," "push," "just-in-time (JIT)," "economies of scale" and "off-shoring."

The result of this study reveals that disruption in a small number of suppliers across any of the analyzed tiers can have a devastating effect on the supply of medical equipment. In such a business environment, one of the key questions facing supply chain managers is how many tiers of the supply chain need to be analyzed to obtain enough information about the structure of the supply chain? We provided a data-driven method that identified the minimum number of tiers to be analyzed to acquire such information. We recommend practitioners establish integration strategies across their supply tiers that includes the convergence tier of the relevant threat model.

The analysis of the effects of disruptions in this paper is primarily based on ATSR and STSR. However, it is noteworthy to mention that we also computed the percent of MSFs with All Terminal Suppliers Reachable (ALTSR). Through our experiments, we observed that ALTSR drops to zero with high probability almost immediately because each MSF depends on thousands of firms. This exhibits one of the limitations of the study, as in real-world operations, firms usually carry buffer inventories and hence may be able to identify alternative suppliers across different tiers. Nevertheless, such extreme experiments can provide beneficial information to identify critical supply paths, considering the high dependencies in the medical equipment's global supply chain. In addition to supply chain tier analysis and random vs. intelligent disruptions, we also provided a novel approach to measure and illustrate the thresholds of supply chain breakdown and fragmentation.

Another contribution of this work is its application in the validation of future simulation algorithms. Our analysis provides benchmark supply chain patterns of behavior to be used in future simulation algorithms to produce more accurate "in silico" models that can better "mimic real data" (De Smet and Marchal, 2010). The findings and methodologies utilized in this study has notable implications for policy makers working on commerce, national security and public health. We illustrate tools to identify central supply chain nodes across multiple tiers of supply and highlighted the vulnerability of supply chain to various disruptions. Also, relying on multiple MSFs does not necessarily diversify the risk as many MSFs share some supply pathways across multiple tiers of backward supply chain. These are some of the topics that policy makers can strategically explore using such networks analytics models.

7. Limitation and Directions for Future Studies

Some of the constraints of this study are related to our data. Our supply chain data includes only the notable suppliers as defined in the paper, and furthermore, the monetary value of supply chain relationships is not available. Another limitation of our supply chain network is that since the data is primarily mined from financial records of the publically traded firms the supply chain network does not include smaller private firms that do not have notable supply chain connections with the publically traded firms.

Despite these limitations, to the best of our knowledge, this is the most comprehensive real-world global supply chain data that can be legally collected within current business practices and legal frameworks. Since we tried to use the most efficient algorithms, we did not face significant computational challenges that may arise from the data's size and complexity. While we could analyze the data across ten tiers for this industry using high-performance personal computers, we recommend researchers to consider using cloud computing for analyzing larger networks.

The present study explored the backward supply chain. Future studies in the area are encouraged to conduct forward supply chains. The study of supply chains across multiple tiers and scales can be conducted at the network level, the process level and the control level (Ivanov and Dolgui, 2021). Since the focus of this study has been on the network-level, the operational parameters have not been considered in the analysis. While this poses limitations for the implications of the work there are fruitful opportunities for expanding the resent work to explore the relationship among the three levels proposed by Ivanov and Dolgui (2021).

While the current research focuses on analyzing nodes, we believe there are fruitful research opportunities in conducting clustering analysis based on community detection algorithms. Future studies are encouraged to explore supply chains' vulnerability when a cluster of firms is affected or when central firms across different communities are affected. Furthermore, this study is based on the analysis of the supply chain networks. Future studies can explore the global supply chains using multi-layer connected networks of business ecosystems.

It this study we proposed analytical tools to identify the survival of firms based on access to average or some suppliers. In future studies we plan to identify the firms that survived some level of failure or attacks. We are interested to explore various characteristics of this firms to identify potential supply chain, firm specific and/or industry-specific characteristics that can contribute to higher probability of enduring such events.

While most studies in this domain explore the effect of disruption, there has been a gap in the literature on exploring post-disruption supply chain management (Ivanov, 2021). The research methodologies employed in this paper are compatible with additions to simulate random as well as intelligent recovery. We plan to conduct such studies in the future with the goal of identifying the optimized recovery paths.

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Supplementary file:

Python codes included as supplementary material

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Appendix 1

Supply Chain (SC) Ability Facets: Managing Disruptions

Supply Chain Abilities	*Meaning*	*Aim*	*Source*
Resiliency	SC's ability to "to recover their performance after having absorbed the disruption effects" and "return to its original [or desired] state after being disturbed."	Recovery	Baz and Ruel (2021); Peck (2003)
Robustness	"S.C.s' ability to maintain its planned performance following…disruption(s)."	Maintain operation	Baz and Ruel (2021)
Agility	SC's ability to "rapidly align the network and its operations to the dynamic and turbulent requirements of the demand network" and "shifts in supply".	Rapid response	Ismail and Sharifi (2006); Kitchen and Hult (2007)
Vulnerability	SC's "exposure to serious disturbance, arising from risks within the supply chain as well as risks external to the supply chain."	Measure of risk	Peck (2003)
Flexibility	SC's ability "to respond to changes in the volatile environment, without excessive performance loses."	Manage minor, short-term disruption	Delic and Eyers (2020).
Adaptability	SC's ability to "reshape" and "adapt to [an] uncertain environment in order to reduce any adverse impacts…without ties or legacy issues or regard to how the chain has been operated previously."	Manage major, long-term disruption	Chan and Chan (2010); Kitchen and Hult (2007)

Appendix 2.

Firms' distribution across tiers