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Assessing Supply Chain Resilience During the Pandemic Using Network Analysis

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***Abstract*—Disruptions induced by the COVID-19 pandemic have wreaked havoc in supply chain networks. To gain an understanding of the dynamics that had been at play, we construct a real supply chain network (scale-free) based on a seed firm (Apple), its customers, and its first- and second-tier suppliers, yielding a network of a total of 883 firms. We then use visualization to derive insight into various network characteristics and develop an agent-based model to capture the disruption of the network over a period of 400 days from the onset of the pandemic. The disruptions experienced by firms depend on the stringency of measures taken to curb the pandemic in their respective countries and the severity of disruptions experienced by suppliers in a specific region. We specifically find that spatial complexity, degree centrality, betweenness centrality, and closeness centrality have changed significantly throughout our observation period. We thus subsequently theorize on the influence of some of these characteristics on supply chain resilience (SCRes), and through our empirical tests, we find that, at the network level, Average degree and spatial complexity significantly influence SCRes. At the firm-level, we find that powerful firms within the network influence SCRes based on their betweenness centrality and closeness Centrality. Implications for managerial practice and academic research are discussed.**

***Index Terms*—Network analysis, pandemic, ripple effect, supply chain resilience (SCRes), visualization.**

I. Introduction

THE impact of the COVID-19 pandemic on global supply chains has illustrated their interdependence and complexity, contributing to the risk that needs to be managed [1]. What makes this management so challenging is that a small disruption anywhere in the network, no matter how far from the focal firm, can have significant ripple effects throughout the supply chain [2]–[4], rendering these potential distant disruptions critical yet difficult to assess and mitigate. Possessing supply chain resilience (SCRes), which entails developing capabilities enabling firms to resist and recover from disruptions, has therefore become imperative [5], [6]. Resilience can be built at the firm level, through investments in capacity management, resource allocation and inventory management, and at the network level, through supplier development programs, network visibility initiatives [4], optimized network structures [7], and viewing networks as complex adaptive systems (CASs) [8]. We label this resilience at the network level supply chain network resilience (SCNR).

The repercussions of the COVID-19 pandemic exposed many supply chains and demonstrated the need for further improvements in SCRes. For example, Hyundai had to shut down its South Korea manufacturing sites since it ran out of components from China in February 2020 [9]. A month later, operations of retailers like Amazon and Walmart got disrupted, scrambling to get needed products on their shelves [10]. Repercussions continue to be reported, such as Boeing delaying its deliveries in January 2021 [11]. While 27% of organizations responding to a survey by the Business Continuity Institute [12] reported experiencing ten or more disruptions in 2020 due to the pandemic, a total of 40% of these disruptions occurred beyond tier 1 suppliers, which makes these disruptions more difficult to manage and plan for. Calls have therefore been issued to examine the resilience of supply chain network structures [8], [13]—A topic that has been elevated now due to the pandemic. What made navigating pandemic-related supply disruptions even more challenging is the fact that the pandemic impacted both supply and demand simultaneously, in addition to multiple disruptions happening at the same time at different locations [14]. While companies struggled significantly, looking back at the dynamics experienced offers a rich context to investigate SCRes and develop recommendations for moving forward.

While studies have investigated network disruption models (e.g., [2], [15], and [16]), to the best of our knowledge, none of the studies have captured real-world disruptive events. This is, therefore, the research context we focus on in this article, aiming to provide guidance for more resilient network structures. The specific research questions we aim to answer are as follows.

1) RQ1: As the pandemic progressed, how were supply chain network structures influenced by the associated dynamics?
2) RQ2: What supply chain network characteristics were most influential in contributing to SCNR during the pandemic?

In answering these research questions, we work to create a better understanding of resilience and how to capture it, specifically by considering the ripple effect. We also recognize that not all disruptions are alike—while some have only a minor impact

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on a few select stakeholders, others can impact the entire supply chain. We frame our investigation within the network literature in general, and the ripple effect more specifically. Our empirical data is combined into an agent-based model, also leveraging visualization to develop deeper insights.

The rest of the article is organized as follows. Section II proceeds with a review of the literature, followed by Section III providing the model architecture. Section IV presents the analysis and results. Section V reflects on theoretical and managerial implications and Section VI concludes the article with its limitations.

II. Literature Review

A. SCRes From a Network Perspective

SCRes has been investigated from a variety of perspectives, including ecological, engineering, social, psychological, economical and organizational [5]. Primary angles employed have been the resource-based view and dynamic capabilities, untangling aspects that help to minimize vulnerabilities [17], [18]. Capabilities that were identified include agility, integration and reengineering [19], and event readiness, responsiveness and recovery [5]. The source of SCRes is founded in several roles and functions, which are grouped under the broader construct of functional capabilities; these can include procurement [20], buyer-supplier relationships and collaboration [21], sourcing strategy [22], supply chain visibility, cooperation, and information sharing [23], with many of them being located at the inter-organizational interface. While research is rich in the identification of these dimensions at the firm level, research that looks at SCRes at the supply chain network level is scarce. Further research in this domain has therefore been called for [24].

Choi *et al.* [25] helped jumpstart this research agenda by considering supply networks as CASs. Inherent to CAS is that they are not the outcome of a single entity, but emerge based on network agents' activities. Since changes in the network are often beyond the awareness of the firm, Choi *et al.* [25] viewed these supply chain networks as CAS. Carter e*t al.* [8] took this work further and viewed agents as grappling with the tension between control and emergence. While a firm has control over its internal operations, making planning doable, the emergence of issues beyond the visible horizon of the firm in the external environment creates challenges, necessitating the firm to adapt. Further complicating aspects include the existence of both a physical supply chain and a support supply chain, visibility into which is generally bounded by a single organization. While the physical supply chain involves products and materials, the support supply chain consists of firms assisting in this primary endeavor, such as financial and consulting firms. This complexity is our current reality, which is why we focus on the network perspective to investigate SCRes within this context. We find our approach corroborated by Tukamuhabwa *et al.* [26] review article, which positioned the CAS lens as the most appropriate to study SCNR.

Two perspectives of SCRes are prevalent in the literature [6], with the first one representing the "engineering" form of resilience, which focuses on "bouncing back" to the equilibrium state, and the second one being the "social-ecological" form of resilience, which resists disruptive change by adapting through the process of renewal, reorganization and development—this can potentially lead to a state that is quite different from original equilibrium. With this framing, Wieland and Durach [6] (p. 2) defined SCRes as "the capacity of a supply chain to persist, adapt or transform in the face of change." Inherent to this definition is dynamism, allowing the boundaries of the system to change by including or excluding agents (firms) and/or by adding or eliminating connections among agents [25]. From an SCRes angle, this can be conceptualized through the adaptive cycle approach [27], which is a concept borrowed from the natural sciences. It suggests that the resilience of a CAS, such as a supply chain, is not fixed, but expands and contracts over time. Akin to this, Hosseini *et al.* [28] used systems theory to conceptualize SCRes. We thus suggest that large-scale supply chain network disruptions due to COVID-19 can be viewed through the CAS lens [6], while at the same time acknowledging that disruptions can come in all shapes and sizes [29]. This means that what may work for one firm, may not for another firm.

Network theory has been a primary framework to analyze supply chain network disruptions and SCNR [13]. In this vein, Margolis *et al.* [7] designed a model for a resilient supply chain network, and Hosseini and Ivanov [30] developed a resilience measure considering a Bayesian network approach. Cardoso *et al.* [31] assessed network resilience metrics of supply chains under demand uncertainty, and Dixit *et al.* [32] assessed pre-and-post disaster SCNR based on network theory. Similarly, Li and Zobel [15] explored risk propagation and SCRes. Basole *et al.* [33] also highlighted the importance of network structure and its effect on performance. In applying network theory, these studies had to assume the homogeneity of nodes, which is an assumption that can be relaxed when using agent-based modeling. With this approach, the interdependence of nodes can be captured. This was for instance done by Zhao *et al.* [34], who analyzed the resilience of a supply chain network, and Nair and Vidal [35], who used CAS theory to model a simulation-based system to find out whether there is a significant association between network characteristics and supply network robustness measures. Basole and Bellamy [2] also developed a model based on heterogenous nodes to explore risk diffusion. In addition to these network models, relatively few studies used survey-based instruments to analyze supply chain characteristics during disruptions. Examples here include Bode and Wagner [1] and Brandon-Jones *et al.* [36], who established supply chain complexity to be related to upstream disruption frequency. An overview of articles on SCRes taking a network perspective is given in Table I.

Several of the above-cited studies have used network level metrics to assess resilience, including network density, node criticality and complexity [37], capturing networks with many critical nodes tend to suffer more severe disruptions than networks with less critical nodes [38]. However, most of these studies do not incorporate the cascading failure of nodes, commonly referred to as the ripple effect. Exceptions include Zhao *et al.* [16], who modeled a complex supply chain network system using agent-based modeling to understand supply chain's

TABLE I
LITERATURE ON SCRES TAKING A NETWORK PERSPECTIVE

Article	Theory	Type	Network size
[1]	Complexity theory	Empirical; Survey	396
[15]	Ripple effect; Network theory	Empirical; Simulation	100, 300, 500
[16]	Complex adaptive systems	Empirical	2971 nodes
[18]	Systems theory, Resource based view	Empirical	Case based
[19]	Social network analysis	Empirical	33 firms
[28]	Ripple effect, Network theory	Review	-
[33]	Network theory	Empirical	114
[35]	Complex adaptive systems	Simulation	18 modes
[38]	Complexity theory	Conceptual	NA
[39]	Ripple effect, Network theory	Empirical; Simulation	11
[40]	Grounded approach	Empirical; Survey	10
[43]	Bayesian network	Simulation	5
[46]	Transaction cost economics, Knowledge based view, Network theory	Empirical	867
[60]	Ripple effect, Grounded approach	Case based	7 case studies

adaptive behavior during disruptions, and Li and Zobel [15], who explored the network characteristics of SCRes based on synthetic networks.

B. Ripple Effect

Risks originating in seemingly unrelated and distant parts of the network can quickly propagate and cripple the entire network through the disruption's ripple effects [2]. The traditional view of a supply chain network subscribes to a unidirectional flow of materials and information. However, real-life supply chain networks are complex and non-linear, also exhibiting circular flows. As such, a disruption's ripple effect is more severe when it occurs inside (as opposed to outside) circular flows [39]. It is thus expected that when multiple disruptions occur in a supply chain network, the impact of the disruptions should be greater than if a single disruption occurs, given that the disruptions occur in similarly prominent network locations. Within this context, the concept of the ripple effect describes the impact of a disruption's propagation on supply chain performance, including its structural design and planning parameters [3], [4], [40]. The ripple effect is different from the bullwhip effect in that the ripple effect arises from disruptive low probability events affecting the structure of the supply chain, with the possibility of severe long-term effects amid short-term effects [3]. A relatively few studies have measured the effect of such propagation. For example, Osadchiy *et al.* [41] considered the propagation of systematic risk to reflect in production decisions and order aggregation, and Levner and Ptsukin [42] developed an entropy-based model to manage ripple effects of environmental risks. Further, Garvey *et al.* [43] suggested that Bayesian networks lend a natural fit for the goal of measuring risks within a supply chain. If constructed according to a supply network structure, Bayesian networks represent a snapshot of a firm's supply chain risk profile. Hosseini *et al.* [30] and Shi and Mena [44] both used a Bayesian approach to develop a SCNR assessment metric. Ivanov [45], using a discrete-event simulation model, found that the ripple effect enhances the performance impacts of disruptions, making firms more vulnerable under a single sourcing policy. Using a similar model, Ivanov [14] considered a single industry with strict assumptions and developed predictive insights with respect to supply chain disruptions due to COVID-19.

Overall, while work on the ripple effect has been proliferating, research is scant that considers networks of heterogeneous agents using real-world data. An exception forms again Li and Zobel [15], who investigated overall SCNR using several metrics in the presence of the ripple effect. In addition, what characterizes most empirical studies in this domain is that a static approach to assess SCNR was taken, with relatively few studies considering the impact of risk propagation in a complex network context [2], [15], [16]. The importance to do so is however given, since it makes the network model more realistic. We also note that the ripple effect is not focused on risk propagation itself, but on the consequences of risk propagation in the supply chain network, which directs further attention to the resilience attribute. Since we aim to understand how supply chain network structures were influenced during the pandemic taking network perspective, considering the ripple effect becomes imperative.

C. Measuring Supply Chain Network Resilience

The resilience of a supply chain network (which we consider consisting of several individual supply chains) is dependent on the following network characteristics.

1) *Network Type:* SCNR is affected by network type [13], which is based on the degree of the node distribution. Based on the classification by Kim *et al.* [13], network types can be scale-free, block-diagonal, centralized and diagonal. Other classifications, such random graph, small-world [2], [35], and hierarchical [34] are also present in the literature. The scale-free pattern has few nodes with disproportionately many connections, which generally resembles a power-law distribution. The scale-free design has been considered as an attack-tolerant complex network [13], with however Zhao *et al.* [34] countering that scale-free networks are vulnerable to targeted disruptions.
2) *Network Density:* Craighead *et al.* [40] identified supply chain network density as the clustering of suppliers in different parts of the world. We view this explanation closer to the definition of spatial complexity. Instead, we capture network density as the ratio of the number of existing edges to the number of total possible edges at a given time period in the network [31], [13].
3) *Supply Chain Complexity:* Supply chain complexity is the sum of the total number of nodes and edges [31]. It can be further expanded to node complexity, i.e., the total number of nodes in the network, and flow complexity, i.e., the total number of edges in the network [35]. Another related metric is Average Degree, which refers to the ratio of the total number of edges to the total number of nodes in a given period. Complexity can also be captured at the

supplier base level. For example, Horizontal Complexity is the number of suppliers directly connected to the focal buyer [46], [1], while Vertical Complexity refers to the depth of the supplier base, which reflects the number of tiers in a supply chain [1]. Spatial Complexity refers to the level of geographical spread of suppliers [1].

4) *Path Length:* Path length indicates the average number of firms that must be traversed between any two firms selected at random. The diameter of a network is the maximum of the shortest path length between any two nodes [34], [16].
5) *Clustering Coefficient:* This captures the average probability of two neighboring nodes that are connected to a given node, which are also connected to each other [16].
6) *Network Centralization:* Network centralization metrics are assessed at the node-level and capture the extent to which overall connectedness is organized around particular nodes. Specifically, betweenness centrality assesses how often the nodes in a network lie on the shortest path between all combinations of network node pairs [13], [15]. Degree Centrality is defined by the number of a node's edges, which, in a directional network, depends on the flow initiated (out-degree) and the flow received (in-degree). In-degree Centrality reflects the degree of difficulty when managing incoming flows from suppliers. Out-degree centrality reflects the level of difficulty in managing customer needs [13]. Degree centrality is linked to node criticality, where nodes that distribute material to many other nodes are considered to be more critical [25], [32]. Closeness centrality measures how close a node is to all other nodes in the network beyond the nodes that it is directly connected to [13]. Eigenvector centrality is based on the connections to high-scoring nodes, which contributing more to the score of a node than equal connections to low-scoring nodes. In this purview, Kim *et al.* [13] suggested that network metrics do not consistently nor reliably predict network resilience. Interestingly, denser or merely more complex networks do not necessarily have higher resilience.
7) *Supply Chain Network Resilience:* There are several definitions of SCNR in the literature. For example, Kim *et al.* [13] defined it as the ratio of the total number of node/edge disruptions that do not result in a network disruption to the total number of node/edge disruptions. It is also defined as a function of the service level during disruption [47], or as the demand-weighted connectivity [7]. Li and Zobel [15] considered three dimensions: robustness, recovery time, and average performance retained over time. In their context, robustness is reflective of the number of healthy nodes, the size of the least connected nodes, and the ratio of the size of the least connected components to the average path length. Zhao *et al.* [34] suggested the availability of suppliers to demand nodes, the largest connected network, and the average path length as resilience indicators. Dixit *et al.* [32] developed a formula combining connectivity, size, centrality and density. We leverage this insight to develop our model in the following section.

III. Network Construction and Model Development

A. Data Collection

Secondary data from Thomson Reuters' Refinitiv Eikon database was used[1] to construct the network. The use of such secondary data available from vendors such Mergent Horizon, Compustat, Bloomberg SPLC, and Thomson Reuters, has become a popular approach for capturing supply network structures [2], [8], [16], since it allows for the collection of data beyond the first supplier tier. The Thomson Reuters database provides information about competitors, customers, and suppliers under the category of "peers and valuation." For each pair of companies, it collects information from related documents (e.g., news, filings), and estimates the probability that there is a valid supplier-customer relationship. This estimation is based on the evidence snippets collected and takes into account the source type. An aggregate score called "confidence score' is created that ranges from 0 to 100%, depicting the confidence associated with the presence of the buyer-supplier relationship.

We collected data by using a snowballing approach suitable for collecting large scale network data [48]. Our focal company or seed node is Apple, which we chose for two reasons. First, it is the most valuable company in the world [49], and thus understanding its supply chain network structure would be valuable. And second, Apple's supply chain experienced numerous disruptions during the pandemic [50], making the company a formidable subject to investigate its SCNR. As such, Apple had to postpone production due to supply and demand disruptions as a result of the pandemic in 2020 [51], primarily due to the firm's reliance on China.

We also note that the choice of the focal company is not relevant when the network is large, as it only serves as a seed node [16]. At the time of data collection in March 2020, there were 302 suppliers listed in the database. We only selected suppliers that had a Confidence score of more than 50%, yielding a total of 204 first-tier suppliers. We matched this list with the list of manufacturing suppliers provided in Apple's 2019 sustainability report [52], which yielded an overlap of more than 50%. That this percentage is not larger can be attributed to the fact that the list of manufacturers in Apple's sustainability report included only those that produced physical goods. As such, our list of suppliers also captured suppliers in the support supply chain. The Thomson Reuters database provides comprehensive data in this regard.

Similarly, for the list of 204 first-tier suppliers, we collected a list of their suppliers (second-tier suppliers) using the same confidence score rule, which was followed by a validation of the firms' existence. Firms with no or incomplete information in the database were removed. The final network is based on a total of 22 customers, 204 tier-one suppliers, and 736 tier-two suppliers.

[1]Thomson Reuters' Refinitiv Eikon - [Online]. Available: https://eikon.thomsonreuters.com

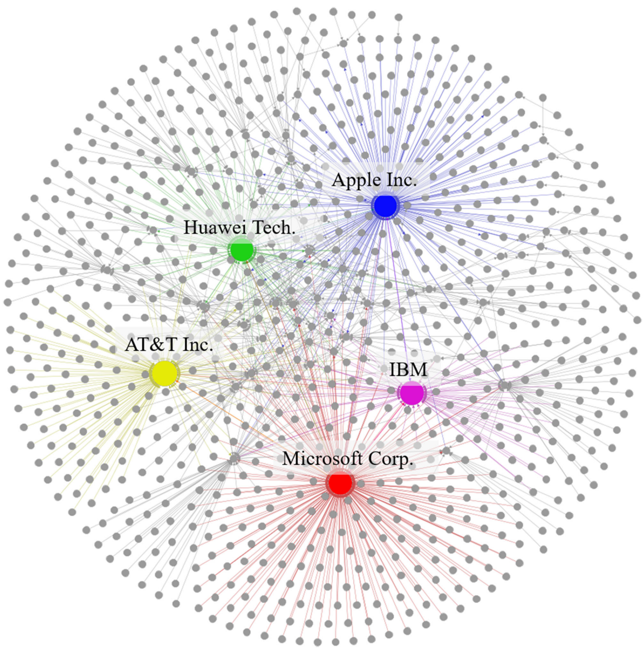

Fig. 1. Network structure of Apple Inc.

TABLE II
TOPOLOGICAL CHARACTERISTICS

Network characteristics	Value
Nodes	883
Edges	1298
Average Degree	1.47
Diameter	7
Average Path Length	3.072
Density	0.002
Clusters	12
Average Clustering Coefficient	0.079

This yields a total of 883 unique firms and 1298 buyer-supplier relationships. The firms are headquartered in 36 countries and cover 91 industries, with Software (19.36%), IT Services and Consulting (11.77%) and Semiconductors (11.09%) being the top three industries. This richness of the data allows us to analyze resilience beyond the visible horizon of the focal firm.

The initial network diagram is shown in Fig. 1. The supply chain network can be denoted by a directed network $G = (N, E)$, where N represents the set of nodes and E represents the set of edges. Each node $n_i \in N$ represents a firm, and each directed unweighted edge $e_{i,j} \in E$ indicates a buyer-supplier relationship, where n_i is the supplier for n_j.

B. Topological Characteristics

The initial network characteristics at time t_0 of our analysis period is given in Table II. We use Gephi 0.9.2[2], to analyze the topological characteristics. Such topological analysis can provide invaluable insight into supply chain networks and their robustness against disruptions [53]. All network characteristics are explained in Section II-C except Clusters. Clusters are calculated

[2][Online]. Available: www.gephi.org

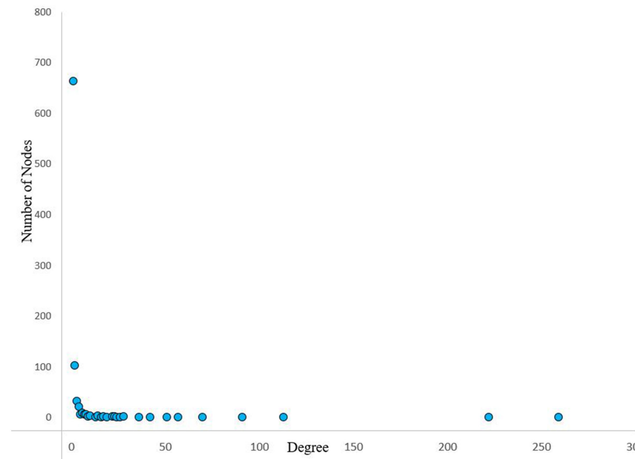

Fig. 2. Degree Distribution.

using the Modularity function, which uses a heuristic algorithm [54] to identify the community structure in a large network. It initially identified 12 clusters. On average, two nodes have approximately two nodes in between and a maximum of five.

We can estimate from Fig. 2 that the network follows a power-law distribution, which is characteristic of scale-free networks. Very few nodes have a high degree of surrounding neighbors, with most of them having few neighbors. Only Apple, Microsoft, and AT&T have a degree higher than 100. AT&T is linked as a tier 1 supplier, a tier 2 supplier, as well as a customer, while Microsoft is linked as a TIER 1 as well as a tier 2 supplier. Similar findings are reported by Zhao *et al.* [16] when analyzing Boeing's supply chain network, i.e., the fact that a firm's competitor can also be an upstream supplier. This finding highlights that real-world network is highly complex and close examination is required.

C. Model Development

Our study is exploratory in nature, as the main objective is to understand how a large-scale real network navigated disruptions during the COVID-19 pandemic. As discussed above, disruptions of extreme nature have a ripple effect that spreads through the supply chain. The measures taken during the COVID-19 pandemic by most countries are expected to have had such a ripple effect, with for instance firms being shut down or operating at reduced capacity. Other disruptions are in the form of border closures impacting delivery and service levels. Previous studies considering the ripple effect used system-dynamics, discrete-event simulations, or agent-based modeling [3]. Bayesian network modeling has also been used [55], which relies on a conditional probability to capture risk propagation. This is however difficult to assess in a large real-world network, and the approach is not able to capture temporal dynamics [30]. We therefore leverage agent-based modeling to simulate actions and interactions of autonomous heterogenous agents. In CAS, combinations of approaches can imply multi-directional causalities, as well as simultaneous and time-lagged effects between agents [38], [56]. This also increases the model's realism, which

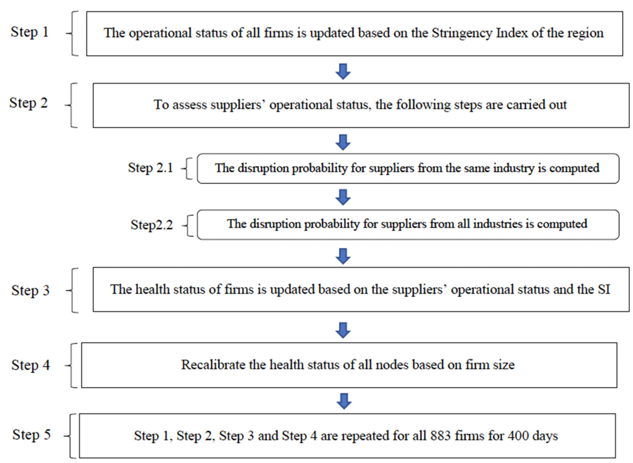

Fig. 3. Model development.

is made possible by the incorporation of empirical data to reflect real-life settings. We apply these principles when designing our network.

Specifically, the model simulates how a supply failure propagates through the agents due to an increase in lockdown policies across the countries of operation. An assumption we make is that firms are operating in the country of their headquarters, which however may not be entirely correct. For example, 3M, a direct supplier to Apple, is headquartered in the United States, having four manufacturing facilities in the country and three outside. Similarly, Darfon electronics is headquartered in Taiwan, with one manufacturing location in Taiwan and one in China. However, since our sample did not include a firm that does not operate where they are headquartered, we believe that the assumption does not violate reality too significantly.

In our model a firm/node represents an agent in the supply chain that faces supply disruption risks from two sources: a) the stringency of measures in a country to curb the spread, as result of which the firm/node must shut down or operate at a reduced level, and b) the severity with which suppliers are impacted in their respective region, thus impacting the delivery of the product or service. This represents a realistic depiction of the situation during the onset of pandemic and is still prevalent in regions in 2021 [57]. We captured the severity of lockdown policies of firms' countries based on the stringency index (SI) calculated by the"oxford coronavirus government response tracker" project [58]. The SI returns a composite score between 0 to 100, based on nine parameters: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls. The dataset starts with January 21, 2020, which is nearly a month after the disease was first identified in Wuhan, China, and ends with February 23, 2021, capturing a 400-day period.

Within this background, the following five steps were applied to construct our model (see Fig. 3). First, most operational research investigating infectious diseases categorizes a population into groups based on the level of infectiousness to enable decision-making; these levels can include susceptible-infected, susceptible-infected-susceptible, susceptible-infected-recovered [58]. Following the same logic, Basole and Bellamy [2] developed a good, moderate and toxic state for agents in a supply chain network. To model the ripple effect, we thus classify in step 1 the operational status of nodes based on the SI into three statuses: fully operational (value $= 1$, if $0 \leq \mathrm{SI} < 25$), semi-operational (value $= 0.5$, if $25 \leq \mathrm{SI} < 50$), and shut down (value $= 0$, if $50 \leq \mathrm{SI} \leq 100$).

Second, we assess the suppliers' operational status (i.e., the ability to supply) in step 2. With firms sourcing similar products or materials from multiple suppliers, we group suppliers based on the industry they belong to and then assess their disruption probability (step 2.1). If one of these suppliers is shut down, others can enhance their capacity to accommodate if they are operational. Therefore, if all suppliers from a particular industry are operational, a firm's supply remains undisrupted. Further, if a firm has two suppliers that are both semi-operational (i.e., value $= 0.5 + 0.5 = 1$), this is equivalent to one supplier being fully operational. Based on the value of operational statuses, we obtain a probability of supply in a specific industry getting disrupted in step 2 as

$$\mathrm{Pr}_{\text{industry\_supp\_disrup}} = 1 - \frac{\text{suppliers operational}}{\text{total number of suppliers}}. \tag{1}$$

For our model, we assume that industry-specific suppliers are disrupted if their probability is greater than 0.33 for the product, material or support service to be supplied to the firm; otherwise, they are undisrupted. Similarly, a firm sources different ranges of products, materials or services to ensure the supply chain runs efficiently, with these suppliers however being in different industries. We therefore also compute the disruption probability for suppliers from all industries (step 2.2). Specifically, we define the probability that the supply to a node gets disrupted as

$$\mathrm{Pr}_{\text{supp\_disrup}} = -\frac{\text{number of industry specific supply operational}}{\text{total number of supplier groups}}. \tag{2}$$

To illustrate this within the context of our network, Apple has 200 suppliers from 42 industries, with 29 suppliers belonging to the electronic equipment and parts industry. If the value of this industry's operational status is lower than ten, then the industry's supply is considered as disrupted. If 28 out of the 42 industries are non-disrupted, the probability that the supply to Apple gets disrupted is 33%.

Third, as discussed earlier, a firm faces disruption risks from two sources, one being tied to stringent orders in the region aimed to curb the spread and the other being supplier failures. We therefore update the health status of a node/firm based on these two attributes (step 3) (see Tables III and IV). We see from Table III that the statuses are different than the ones previously used (operational, semioperational and disrupted). This is done to capture a firm being able to function. The ability to supply is captured in Table IV. The final health status of a node is obtained by taking the minimum value across the two tables.

TABLE III
SI AND HEALTH OF FIRMS

SI	Status	Value
0	Healthy	3
$0 < \text{SI} \leq 20$	Moderate	2
$20 < \text{SI} \leq 50$	Vulnerable	1
$\text{SI} > 50$	Disrupted	0

TABLE IV
PROBABILITY OF SUPPLY GETTING DISRUPTED AND HEALTH OF FIRMS

$\text{Pr}_{\text{supp disrup}}$	Status	Value
0	Healthy	3
$0 < \text{Pr} \leq 0.2$	Moderate	2
$0.2 < \text{Pr} \leq 0.5$	Vulnerable	1
$\text{Pr} > 0.5$	Disrupted	0

Fourth, organizational size affects the ability to manage risk [16], [60], with larger organizations generally having better capabilities, which can include information sharing and visibility [60]. We take revenue as an indicator of firm size and based on the log-transformed value we categorize firms into three groups: large-size (28 firms), mid-size (718 firms) and small-size (137 firms). We use this to recalibrate the health statuses of all nodes (step 4). For large firms, a downgrade in health status (e.g., from healthy to moderate) due to the above-discussed reasons, is relaxed and therefore its status does not change (i.e., the healthy status remains). In contrast, small firms are downgraded by one level in this instance (i.e., from healthy to vulnerable). Unless observed, mid-sized firms are not forced to change their health status. We developed a time-series of health status values of the 883 firms over the 400 days, with all four steps being repeated for the 833 firms for 400 days (step 5). The network is visualized and analyzed in Gephi 0.9.2.

IV. ANALYSIS AND RESULTS

Our study deploys the dynamic aspect of SCNR in the network through SI, which is an outcome of measures taken to curb the spread of the pandemic. Given that a node/firm is disrupted, it takes some time for the disruption to take effect. Ivanov [14] aimed to predict the impact of an epidemic outbreak, considering different disruption periods in different echelons of a lightning equipment supply chain, considering a lead-time between 4 and 9 days. While lead-times vary significantly across industries, integrating varying lead times would not be feasible in our network due to its large size. We thus assume that there is no time-lag between the SI and its effect on supply disruptions.

The SI unit for magnetic field strength H is A/m. However, if you wish to use units of T, either refer to magnetic flux density B or magnetic field strength symbolized as $\mu_0 H$. Use the center dot to separate compound units, e.g., "A$\cdot$m^2."

A. Visualization

Basole and Bellamy [62] highlighted that visualization is an effective tool that can provide insights into structures, dynamics and strategies. In fact, visualization is considered an integral part of the scientific approach and an effective method to transform data into knowledge [62], [63]. Against this backdrop, visualization can achieve the two primary objectives of the article, i.e., the investigation of changes in the supply chain network structure during the pandemic and the associated network characteristics that influence resilience.

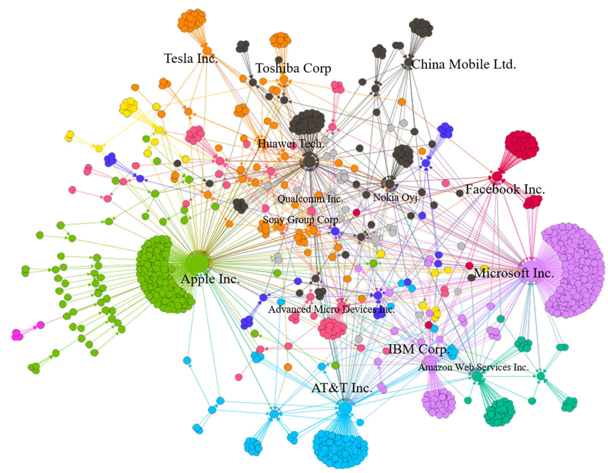

Fig. 4. Supply network structure.

We utilized the Force Atlas2 algorithm, a force-based algorithm that is used for large scale-free networks to spatialize [54]. The algorithm positions the firms based on both attracting and repulsing forces of associated node connections. The result produces visual densities that denote structural densities and the overall network structure of the supply chain. The resulting network structure is captured in Fig. 4, with the associated health status taken at the midpoint of a three-day interval in our timeseries (which ranged from January 2020 to February 2021), illustrated in Fig. 5. In February 2020, it is evident that the health of almost all nodes had started deteriorating, and by March 2020, most of the nodes had become vulnerable. However, the peak of countries' average SI (see Fig. 6) was in April 2020, with the minimum value in September 2020. From November onward, we observe only few nodes recovering from a vulnerable to a moderate state, however reverting back to a vulnerable state in February 2021 as a consequence of an increase in SI due to the second wave of the pandemic. Also, from Fig. 5 we observe that many firms are in a vulnerable (red) state but disconnected from the network (especially in March 2020).

Jones *et al.* [36] noted that as supply chains becomes more global, the uncertainty of product flows increases. We therefore captured spatial complexity (which is sometimes also described as supply base complexity, supply chain density, supply chain complexity, and geographic dispersion complexity) as another network attribute, illustrated in Fig. 7. As can be seen, many suppliers are from the United States (more than 50%), followed by China, Taiwan and the United Kingdom, making the supply network more heavily dependent on the pandemic situation in these countries. In addition, we can see that Microsoft had lost a larger number of suppliers by February 2021 than Apple, which may be due to Microsoft having the largest pool of suppliers in the network to begin with. As such, with more suppliers

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

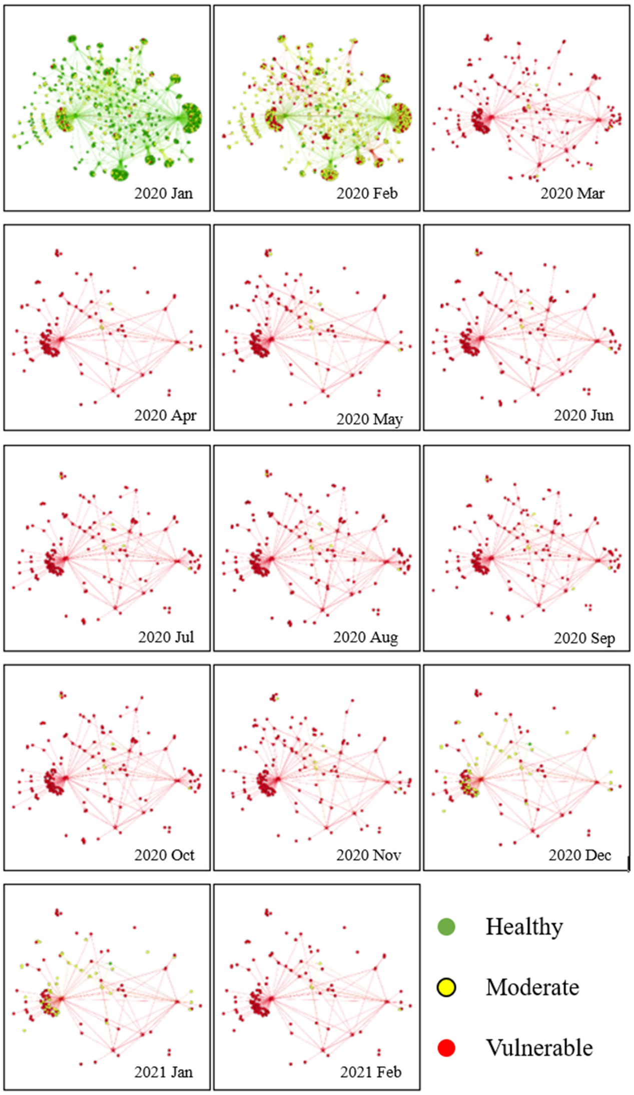

Fig. 5. Network during the pandemic.

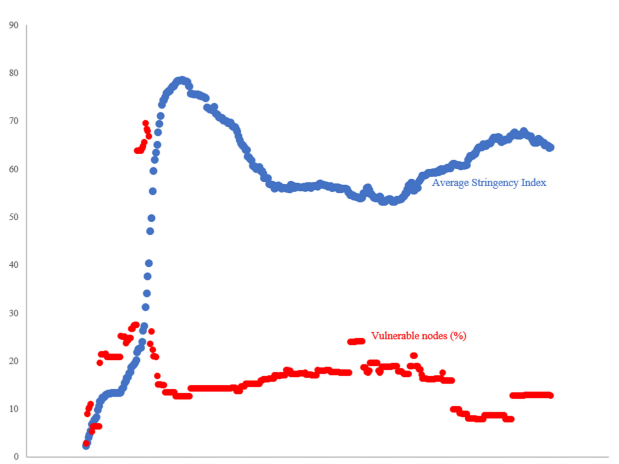

Fig. 6. Average SI progression.

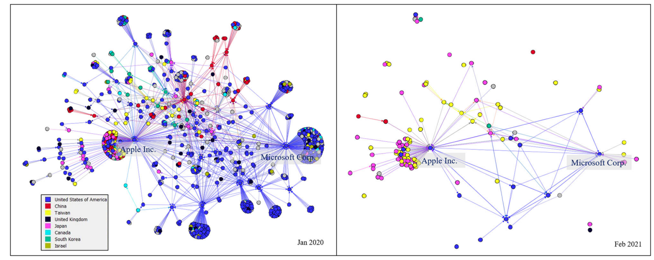

Fig. 7. Network during the pandemic.

in the network, the frequency of disruptive situations, such as inventory obsolescence and stock-outs, may increase. However, our results suggest otherwise, siding with Craighead *et al.* [40], who proposed that the effects of a supply distribution are not as severely felt in a more dispersed supply chain. This is grounded in the notion that if more nodes are concentrated in a region, a single disruptive event can bring down more of these nodes. Considering the ripple effect, Birkie and Trucco [64] observed a similar behavior.

A small nuance to these studies is however that they are within the context of supply chain disruptions, and not resilience, with greater resilience often being associated with better performance during times of crisis. As such, while supply chain disruptions cause damage to a network, resilience captures the effective response to these disruptions, offering an assessment of performance. In this vein, Lu and Shang [46] showed that spatial complexity exhibits a nonlinear influence on financial performance within the context of disruptive events, with their direct effects however being limited to specific regions that experienced a disruption, for instance by a hurricane, forest fires, or floods. This is quite different to the COVID-19 pandemic, which has been causing disruptive effects worldwide. What also needs to be recognized is that supply chain disruptions did not occur only because of the pandemic itself, but also due to country-specific policies aimed at curbing the spread. Therefore, countries that were able to get the spread under control (i.e., countries that exhibited more resilience) allowed trade to continue as much as possible. To enhance the resilience of a supply chain network we thus suggest a geographical dispersion of the supply base, and formally propose the following.

P1: SCNR is positively affected by spatial complexity in the event of a disruption.

In Section II-C, we highlighted several centralization metrics that characterize a network. We compare and analyze some of these metrics and visualize these in charts with respect to three points in time: (a) Initial (t_0) and (b) Mid-April, a time when the SI was at its maximum (t_x); and (c) mid-September, a time when the SI was at its minimum after t_x (t_y). Fig. 8 shows how node health varied with Average Degree across the three points in time. Initially, at time $t0$, we observe many healthy nodes with a high degree. As the network moves from $t0$ to tx, node health deteriorates, as does the degree of the nodes. From tx to ty the health of the nodes becomes somewhat better, and we observe an

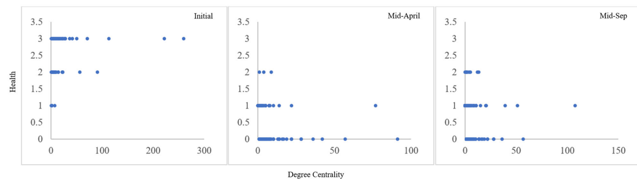

Fig. 8. Average degree versus node health (x-axis: Average degree, y-axis: Node health).

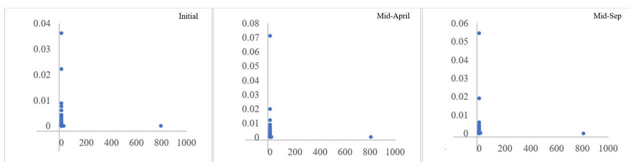

Fig. 9. Frequency versus betweenness centrality (x-axis: Frequency, y-axis: Betweenness centrality).

increase in degree for some of the nodes. The degree of a node is the total number of edges (buyer-supplier relationships), while the average degree of a network is the ratio of the total number of edges to the total number of nodes during the period. Based on this observation, we suggest that the Average Degree of a network influences the resilience of the network. This expectation is in line with Li and Zobel [15], who used simulation to detect a negative relationship between average degree and the number of healthy nodes during a disruption. A large supply chain network is generally scale-free where few nodes have high degrees, in addition to many companies being the end-suppliers with the least degrees. Increasing average degree indicates increasing connections of these low-degree suppliers connecting a greater number of firms within the network. Therefore, as the flow of material increases through these nodes, the disruption becomes more severe and consequently the resilience of the network decreases.

We therefore propose the following.

P2: SCNR is negatively affected by the average degree of the network.

While average network-level characteristics reflect the structure of the network, node-level characteristics, such as betweenness centrality, also reflect the influence of the nodes in the network [62]. Nodes with a high Betweenness Centrality would thus have a greater influence in the disruption [62]. In Fig. 9, we observe that compared to $t0$, when the network structure was undisrupted, we have a few nodes showing high betweenness centrality during the disruption (tx and ty). One might assume that the more often the nodes connect with other nodes in a network, the more resilient the supply network will be. However, Kim *et al.* [13] suggested that there is no correlation between resilience and average betweenness centrality. Nevertheless, it can be argued that betweenness centrality is a node-level metric, and therefore rather than the average value of the whole network, few significant nodes may influence network resilience. The betweenness centrality of a firm is defined by its control and influence in the network [65]. In a large scale-free network, this control and influence over material flow and information is

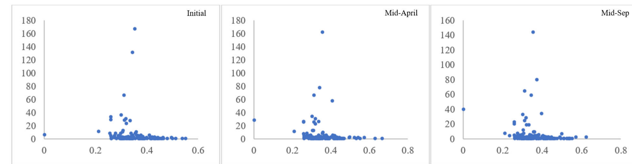

Fig. 10. Closeness centrality versus frequency (x-axis: Closeness centrality, y-axis: Frequency).

skewed in favor of few, select firms, due to the greater number of effective and reliable buyer-supplier relationships they have garnered over time. If these firms remain healthy, the rest of the network remains safe as well [65].

We therefore propose the following.

P3: SCNR is positively affected by the average betweenness centrality of few significant nodes.

Similar to betweenness centrality, another metric at the node-level that characterizes centralization is closeness centrality. This is along the lines of Li and Zobel [15], who reported that along with betweenness centrality, closeness centrality is also influential in determining SCNR. Based on its definition, we suggest that firms that are also connected closely to tier 2 suppliers can exert greater influence in the supply chain. In the event of a disruption, firms with greater closeness centrality are able to process information faster and can make quicker decisions to resist the disruption. A firm with high closeness centrality exhibits more freedom from the influence of others [66], which is a property that also protects connected firms from getting disrupted. We note that during a disruption (tx and ty), few nodes exhibit greater closeness centrality, as can be seen in Fig. 10.

Hence, we propose the following.

P4: SCNR is positively affected by the average closeness centrality of few significant nodes.

B. Empirical Analysis

To investigate our propositions, we ran multiple regression models on the simulated results of the network characteristics obtained from the real-world data. Regression is generally applicable when the underlying model is uncertain, and an explanation of a variable is sought through other variables [67]. Previous efforts to understand different aspects of supply chain disruptions have also used regression [2], [36] by simulating network structure results [15], [16].

Data on network characteristics of the above model were collected, setting the dependent variable as SCNR. As discussed in Section II-C-7., there are a variety of approaches in measuring SCNR. Based on the discussion in Section II-A, especially in light of the definition by Wieland and Durach [6], we consider resilience to be an attribute manifested by several characteristics. As the network persists through a disruption, many nodes become disrupted, while few remain active but disconnected to the larger network. Network resilience is then reflected by the ability to strongly connect to these active nodes. Therefore, we

TABLE V
CORRELATION OF COVARIATES

	AD	CC	BC	SC	ACC
Average Degree (AD)	1.000				
Closeness Centrality (CC)	-0.005	1.000			
Betweenness Centrality (BC)	-0.176	-0.188	1.000		
Spatial Complexity (SC)	0.504**	0.135	-0.606**	1.000	
Average Clustering Coefficient (ACC)	0.653**	0.029	-0.308*	0.250	1.000

*$p<0.05$, **$p<0.01$, ***$p<0.001$.

TABLE VI
REGRESSION RESULTS

	Variable	Coefficient
Control Variable	Average Clustering Coefficient (ACC)	0.143**(0.161)
Independent Variables	Average Degree (AD)	-0.384***(0.010)
	Closeness Centrality (CC)	0.281***(0.010)
	Betweenness Centrality (BC)	-0.137*(0.250)
	Spatial Complexity (SCX)	0.861***(0.000)
Adjusted R^2		0.945
p-value of Rainbow test		0.002
p-value of Breusch-Pagan test		0.006
Durbin-Watson Statistic		2.112

*$p<0.05$, **$p<0.01$, ***$p<0.001$. [Note: The dependent variable SCNR was transformed into an exponential form. All independent variables were transformed to logarithmic forms].

operationalize SCNR by the formula in

$$\mathrm{SCNR} = \frac{\text{Number of strongly connected nodes}}{\text{Total number of nodes existing}}. \tag{3}$$

We retrieved the values of the covariates spatial complexity (SCX), average degree (AD) and other network characteristics using Gephi 0.9.2. For Betweenness centrality (BC) and closeness centrality (CC), we calculated the average values of the common firms that ranked in the top 15 on degree centrality, betweenness centrality, closeness centrality and eigenvector centrality in the initial network structure. They are Apple, Microsoft, Huawei, IBM, and Amazon Web Services. It is suggested that a high clustering coefficient increases the vulnerability of the supply chain [36], which is why we used the average clustering coefficient (ACC) as a control variable. Other studies have considered organizational size [16] and network type [15] as controls. The effect of organizational size is already incorporated in the model, and the network under study follows a scale-free form throughout the disruption. The full model is specified in (4). After transforming the variables to adhere to linearity assumptions, we applied a linear regression model. No strong correlations are present among the covariates (see Table V)

$$\mathrm{SCNR} = \beta_0 + \beta_1 * \mathrm{SCX} + \beta_2 * AD + \ \beta_3 * \mathrm{BC} + \beta_4 * CC + \beta_5 * \mathrm{ACC} + \in. \tag{4}$$

We obtained 57 unique values of SCNR, which is sufficient to effectively run a regression [67]. Table VI gives the results of regression model We considered influential network characteristics that can impact SCNR. We see from the results that three of the four variables under investigation, i.e., average degree, closeness centrality and spatial complexity, significantly explain the dependent variable SCNR. Betweenness centrality was less significant and showed a negative influence on SCNR, contradicting our expectation. Spatial complexity had a higher beta coefficient. We also found the average clustering coefficient, a control variable, to be significant and having a positive effect on resilience. Three out of the four propositions are supported, and all have strong implications, which are discussed later.

V. IMPLICATIONS

A. Theoretical Implications

Our study addressed several important questions. First, recognizing the pandemic as a special type of supply chain disruption due to its global reach and repercussion, we aimed to explore what happens to a global supply chain structure as the pandemic progressed. The answer is more complex than just acknowledging that "it gets disrupted." The disruption of a supply chain network during the pandemic was captured through pandemic control measures in the firms' countries of operation. Based on our agent-based model, we find that the network-type remained scale-free throughout the event, even when the total number of existing nodes came down to 115 (at the highest point of disruption) from an initial 883 nodes. As such, the disruption did not affect the network-type. This phenomenon adds to the literature that has discussed the influence of network-type on disruptions [2], [13], [34].

We also visualized the disruption as a time-series, offering enhanced insights on the health of nodes and their spatial complexity over time. We further addressed the important question on what characteristics influence SCNR. We find that the average degree has a negative influence, spatial complexity has a positive influence, the betweenness centrality of important firms has a negative influence, and the closeness centrality of important firms has a positive influence. We also found the control variable average clustering coefficient to positively influence SCNR. Our theoretical contribution lies particularly in extending the literature on SCRes, by adapting the view of supply chains as CAS [8] and incorporating the ripple effect [3].

While operationalizing the variable SCRes using elements of network theory, we underline the debate on SCRes perspectives related to "engineering" and "social-ecological" resilience [6]. This has been particularly lacking in previous studies. For example, Kim *et al.* [13] definition of SCRes, based on the number of nodes/edges disrupted, considered a network disruption to be binary. As evident from our study, a large network does not become totally disrupted. In addition, Ojha *et al.* [55] resilience index is based completely on "engineering resilience" assuming the initial level of measurement as the optimal level. Similarly, Li and Zobel [15] developed multiple metrics considering an initial level as the optimal state. Other metrics, like time-to-survive and time-to-recover [68], follow the same view. Our conceptualization of the network and its progression through the pandemic captures both perspectives. In our model, the supply chain network at all stages of the pandemic aims to get back to the full health status of all firms, allowing all established buyer-supplier relationships to operate, being only hindered by pandemic control measures. This aligns with the engineering thought of resilience whose capability enables firms to bounce back to their original state.

However, we measure SCNR as the ratio of the number of firms that are connected to the largest forming network relative to the total nondisrupted firms in a time interval, rather than all initially existing firms. This encapsulates the social-ecological way of resilience, which is demonstrated by the ability to persist in the optimal possible manner in the face of change. One may argue that a firm may try to replace a disrupted supplier to adapt to a new optimal state as modelled by Zhao *et al.* [16]. This is valid, but during a prolonged disruption like the pandemic, new suppliers are difficult to on-board and buyer-supplier relationships take time to develop [69]. This is also evident from the focal company in the article (Apple): only 12 new small-sized firms out of a total of more than 200 suppliers were added in 2020. We do however concede that SCNR is just one attribute [5], and our way of operationalization captures only the outcome of resilience, and not the resilience capability itself.

We find spatial complexity as a strong factor that positively affects SCNR (P1). The result is not surprising and supports recent findings by Birkie and Trucco [64] via our modeling of a real-world network. The result however causes some concern over recent calls for reshoring or back-shoring to enhance resilience. Average degree is another factor affecting SCNR. Li *et al.* [37] find that average degree and network type did not explain SCNR of a network better than other influential characteristics, with however Li and Zobel [15] contradicting this. We highlight here that the mentioned studies have simulated networks of a maximum size of 500 across four average degrees: 2; 4; 6; and 8. In this article, based on a real-world network with a network size of 883, the Average Degree does not go beyond 2 at any point during the disruptive event. This is where our contribution lies, with the Average Degree exhibiting a negative influence on SCNR in a scale-free network (P2).

Among previous studies, Kim *et al.* [13] did not find any correlation with SCNR and either Betweenness Centrality or Closeness Centrality. However, Li *et al.* [37] and Basole and Bellamy [62] suggested that influential nodes affect the network's heath. We establish the role of influential nodes in SCNR, with our finding suggesting that in a scale-free network, betweenness centrality of influential firms adversely affects SCNR, while it is the opposite for closeness centrality. It is important to note that the relationship between SCNR and the discussed variables is not linear, and we fitted a regression model only by transforming them.

Our results have also important implications for supply chain management. As such, our first proposition captures that when firms are located in separate geographical regions, the risk of a disruption is spread out. In scenarios like hurricanes, floods, or even a pandemic, one supplier becoming non-operational does not necessarily affect the whole network. However, other factors, like supplier redundancy or ramp-up capacity in the supply network, do play a role. In a supply chain network, there are often "key players" that are boundary spanners between the end consumers and higher-tier manufacturers [65]. Firms with high betweenness centrality scores highlight the significance of these entities, which possess considerable influence and control over the flow of materials and information.

If they get disrupted and their production slows down or, in the worst case, they disappear, other firms are likely impacted greatly. It is thus critical for these key players to remain healthy, so that the rest of the network can stay healthy as well, which is the essence of proposition 3. With this understanding, if we now imagine a supply chain network having the same nodes, but a lesser degree of influence over few organizations, it indicates that higher-tier manufacturers are connected with several other firms. While this scenario is rarely observed in practice, since higher-tier manufacturers generally only have a select number of buyers [70], it would reflect an increase in average degree. In light of our results, this would not favor the resilience of the network. In a supply chain network, there also exist firms that are close but not directly connected. This attribute is indicated by high closeness centrality, allowing firms to have independence and freedom from influence by other firms' actions [66], highlighting the significance of proposition 4. The average clustering coefficient also plays a role in the disruption and the associated robustness [35]. In the context of a supply chain network, it offers speed, information access and resource pooling capacity within the clusters [71], thereby aiding in developing the structural resilience of the network. While the influence of clustering in a supply chain network is highlighted in the literature [34], [72], the reasons for organizations to cluster is an avenue worthy of future research. Regional proximity could be noted as one factor favoring clustering, with however our results in Fig. 7 not providing any evidence for this conjecture.

We also provide a methodological contribution by using visualization as a technique to explore network structure dynamics. Basole and Bellamy [62] had called supply chain researchers to use visualization and network analysis to develop deeper insights. We find a combination of visualization tools and empirical analysis to be a meaningful process to understand supply chain network problems.

B. Managerial Implications

The Global Risk Report 2021, a compilation by the World Economic Forum [73], lists infectious diseases as the risk having highest impact; a significant increase in perception compared to earlier reports. Clearly, epidemics/pandemics are significant disruptive events compared to other supply chain disruptions, and it has been the COVID-19 pandemic that has brought resilience to the fore for many managers. Based on a survey report [74] of 1000 organizations in 2020, only a small minority have been taking necessary actions to be resilient to crises, with as many as 44% of the organizations not mapping their supply chain network. Our article indicates how the mapping of a supply chain network can highlight the positions of other firms in the network, allowing potential proactive mitigation and intervention strategies. Advanced digital technologies can enable this transparency and the ensuing collaboration in the network, to address for instance the repercussions of the ripple effect.

In light of our findings, the geographical dispersion of firms in a large supply chain enhances the ability to tackle widespread disruptions, such as a pandemic. The advice for practitioners is to thus select suppliers with similar capabilities from distant geographies, which would prevent the ripple effect and the spread of the disruption through the network, since a direct supplier that sources from a single origin may have the chance to disrupt the network. Similarly, too many buyer-supplier relationships within a concentrated network increase flow complexity, which is indicated by the average degree. Mapping the flow of a supply chain for all products and services separately [7] should allow managers to disentangle this complexity. Another important aspect highlighted by our study was the role of few, important firms. These firms are powerful intermediaries and are the supply network lynchpins for many firms. Too much influence associated with these firms makes the network vulnerable.

Similarly, few firms in the supply chain are proactively managing indirect suppliers, which may decrease the resilience of the network. Both described situations indicate the necessity of collaboration and visibility, the degree of which could be determined by the identified factors (betweenness centrality and closeness centrality). As such, when firms further develop their supply chain network, betweenness centrality and closeness Centrality metrics can be updated over time. Overall, the idea of a network-level analysis of SCRes through SCNR is to complement firm-level understanding, but the described factors alone are not sufficient to provide resilience for a supply chain—they are however a critical element that should not be overlooked. While these discussed parameters are uncommon in resilience assessment practices, we encourage their application, and hope that our illustration of their value and relevance in this work provides motivation to do so.

VI. Conclusion

Taking a network perspective and considering the ripple effect when considering SCRes was an intriguing context, which we addressed in this article. In doing so, we answered the call for more research on conceptualizing resilience beyond the firm [17]. The pandemic has proven to be a costly affair for supply chains [12], but also offered researchers an opportunity to revisit theories of resilience [6]. Our article captures the essence of this opportunity and offers a practical measure of SCRes in a network. Our motivation to capture the disruption of a real supply chain network as the pandemic progresses was accomplished through visualization, offering a richness to the SCRes literature not commonly present. The work in [12] considered premonition to be careful when drawing linear associations between SCRes and other variables and found this caveat to be true—we directly addressed it while empirically testing our propositions. We believe our study as being one of the first to analyze a real disruptive event and the associated SCNR with empirical data. Our contribution to practice also holds ground as we observe most of the global firms finding issues with compliance of tier 2 suppliers and beyond [12].

Nevertheless, our study was not void of limitations. First, while we considered the heterogeneity of nodes, we did not consider the heterogeneity of edges. We viewed all buyer-supplier relationship as equally weighted. Our logic was that the network disruption due to pandemic control measures was not affected by the strength of the buyer-supplier relationship. However, strong buyer-supplier relationships was invaluable in helping firms manage disruptions. In this vein, research was encouraged to identify appropriate secondary data with which buyer-supplier relationship strength can be assessed, and to incorporate this in our model. Second, our disruption model was based on decision-making logic that reflects our knowledge of supply chain disruptions, as it is difficult to obtain data on actual network mode disruptions. Future research could endeavor to find applicable data to capture this more directly, such as complementing the current dataset with press releases or reports of actual disruptions faced by the firms in the network.

Third, there should be some lag from the time SI increases and when the node gets disrupted. Since the lag could vary significantly depending on country and industry, we simplified the model in this vein. A potential avenue to address this shortcoming was to compare the time when restrictions were implemented to the time when firms in that country first started to experience challenges. Similar as above, this could be derived from press releases or other reports about supply difficulties of firms in the network. Finally, we assumed firms in the supply chain network to be only disrupted at their headquarter location. This assumption should be aimed to be relaxed in future research by taking a more granular firm-level perspective.

Since availability of data on outsourced projects to firms in other countries is extremely limited, this makes the associated network construction rather complex. However, looking back over the last two decades and the abundance of secondary data that has become available, we are confident that such more detailed data will become available in the future, enabling this finer-grained investigation. Another fruitful avenue for future research was the further investigation of the clustering coefficient. What would be particularly intriguing was insight explaining organizations forming clusters in a supply chain network. Overall, we believe that there was significant future scope in exploring how organizational and network level characteristics influence supply network resilience. It is our hope that the present article provides motivation and inspiration to do so.

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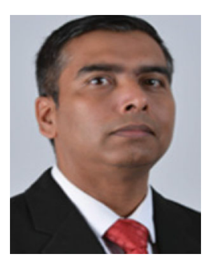

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