IOP Publishing Environ. Res.: Infrastruct. Sustain. 2 (2022) 042001 https://doi.org/10.1088/2634-4505/ac9c8c

ENVIRONMENTAL RESEARCH
INFRASTRUCTURE AND SUSTAINABILITY

CrossMark

OPEN ACCESS

RECEIVED
7 June 2022

REVISED
15 September 2022

ACCEPTED FOR PUBLICATION
21 October 2022

PUBLISHED
10 November 2022

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TOPICAL REVIEW

Characterizing manufacturing sector disruptions with targeted mitigation strategies

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Keywords: resilient systems, risk management, manufacturing, disruption mitigation

Abstract

It has become clear in recent decades that manufacturing supply chains are increasingly vulnerable to disruptions of varying geographical scales and intensities. These disruptions—whether intentional, accidental, or resulting from natural disasters—cause failures and capacity reductions to manufacturing infrastructure, with lasting effects that can cascade throughout the manufacturing network. An overall lack of understanding of solutions to mitigate disturbances has rendered the challenge of reducing manufacturing supply chain vulnerability even more difficult. Additionally, the variability of disruptions and their impacts complicates policy maker and stakeholder efforts to plan for specific disruptive scenarios. It is necessary to comprehend different kinds of disturbances and group them based on stakeholder-provided metrics to support planning processes and modeling efforts that promote adaptable, resilient manufacturing supply chains. This paper reviews existing methods for risk management in manufacturing supply chains and the economic and environmental impacts of disruptions. In addition, we develop a framework using agglomerative hierarchical clustering to classify disruptions using U.S. manufacturing network data between 2000 and 2021 and characteristic metrics defined in the literature. Our review identifies five groups of disruptions and discusses both general mitigation methods and strategies targeting each identified group. Further, we highlight gaps in the literature related to estimating and including environmental costs in disaster preparedness and mitigation planning. We also discuss the lack of easily available metrics to quantify environmental impacts of disruptions and how such metrics could be included into our methodology.

1. Introduction

1.1. Challenges facing manufacturing networks

The pandemic challenges of 2020 and 2021 clearly demonstrated the fragile nature of supply chains and the impact of disruptions on our daily lives. From food to lumber and shipping containers, microchips to automobiles, healthcare supplies to patio furniture, the COVID-19 pandemic disrupted manufacturing systems and surrounding infrastructure on a global scale (Navarro 2020, Pujawan and Bah 2021, Redman 2021). However, the challenges that result from interruptions have existed long before the COVID-19 pandemic. According to the National Oceanic and Atmospheric Administration (NOAA), there have been 332 natural disasters since 1980 resulting in approximately $2.275 trillion in overall damages to the United States (NOAA 2022). An international disaster database from the Centre for Research on the Epidemiology of Disasters (CREDs) recorded less than 200 global disasters per year in the 1980s and over 300 in the 2010s. U.S.-centered natural disasters have quadrupled over the past 40 years, going from 2.7 yr^{-1} to 10.5 yr^{-1} (Ritchie and Brindley 2007). Federal Emergency Management Agency statistics about businesses hit by

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disasters show that roughly 40% do not reopen after a disaster and 90% fail within two years (Access 2018, Katsaliaki *et al* 2021). In addition, these disruptions have a broad range of negative effects including financial, access, and environmental impacts, among others. The alarming growth in the type and number of disruptions complicates planning efforts and will lead to increased losses in the absence of efficient systems that reduce complexity for policy makers.

These problems are only worsening as worldwide supply chains become increasingly complex, extended, vulnerable, and fragile to both global and local disruptions such as weather events (e.g., hurricanes, flooding), climate change (fires, droughts), interruptions to shipping, cyberattacks, and industrial accidents (Manners-Bell 2014, Tukamuhabwa *et al* 2015). For instance, the Ever Given cargo ship, which was stuck in the Suez Canal for a week in 2021, resulted in financial losses to global trade estimated at $9 billion per day—illustrating how the interconnected nature of supply chains increases global supply chain vulnerability (Harper 2021). Further, these reported losses can be considered lower bound estimates focusing on financial costs; they do not include any environmental ramifications, such as the potentially prolonged emissions by the Ever Given and other cargo ships that were unable to transit. These conservative cost estimates, which are very common, raise concerns about a lack of proper measures for environmental cost accounting when investigating disruption effects.

The combined effects of large-scale interruptions with the global nature of manufacturing supply chains have led some government agencies, non-profit organizations, and companies to investigate supply chain impacts from climate change, the rise of the Internet economy, the COVID-19 pandemic, and growing cyber threats (MH&L 2016). The need to develop resilient and robust manufacturing networks has grown in recent years. Innovations in the Internet economy (next day delivery), just-in-time production (e.g. the Kanban system), and multi-tiered supplier networks focused on production cost-cutting have led to supply chains that are vulnerable, stressed, and easily disrupted (Zhu *et al* 2020). Cost reductions have led to the outsourcing, offshoring, and concentration of many manufacturing and research and development activities to lower cost and/or highly skilled countries (Grimes and Du 2020, Katsaliaki *et al* 2021). As of 2017, the bulk of semiconductor foundry activity was located in Taiwan and China, with the largest company, the Taiwan Semiconductor Manufacturing Company, accounting for more than 50% of global revenue (Grimes and Du 2020). Similarly, Japan makes 100% of the world's supply of protective polarizer film for LCD (Liquid Crystal Display) displays, 89% of aluminum capacitors, and 72% of silicon wafers (Hung and Yang 2003, Sheffi 2020).

Industry experts suggest that the trend towards lean manufacturing has exacerbated the consequences of disruptions to supply chains (Wang 2016). These vulnerabilities have become more exposed due to a rising number of so-called 'black swan' events, described as highly unlikely but extremely high impact events (Taleb 2007) such as but not limited to the 2011 Japan compound disaster which included an earthquake, tsunami and nuclear accident and the COVID-19 pandemic. In Akkermans and Van Wassenhove (2013), the authors define 'gray swans' as events arising from a fluke combination of unlikely occurrences and point out that our complex supply chain environment makes them more likely to occur. Some gray swan examples include the 2001 'Internet bubble crisis' and the 2008–2009 'credit crisis,' both of which led to a sharp drop in demand for integrated circuits that cascaded down to multiple manufacturing industries and their supply networks. Understanding the different disruptions that plague our complex manufacturing systems is therefore essential, and properly evaluating their impacts can make our supply chains more adaptable and resilient.

Transient, reactive solutions implemented during supply chain disruptions, if not properly considered, can lead to significant social, environmental, and econmic losses. This is because during a disaster, decision makers have limited ability to analyze or understand its long- and short-term ramifications (Finucane *et al* 2020). An example of a reactive policy is the Coastal Buffer Zone, which was implemented to mitigate the effects of the 2004 tsunami in Sri Lanka and prevent people from returning to risk-prone areas. While this policy had the short-term benefit of bringing people to safety, it led to several long-term issues including increased socio-economic disparities and displacing populations further from the coastal resources on which they depended for their livelihoods (e.g. fishing) (Rice and Haynes 2005, Finucane *et al* 2020). While environmental effects were not explicitly measured, these relocations increased travel distance by vehicles and thus produced more emissions. The above example illustrates how poor and incomplete planning can lead to a disruption with more serious and unintended negative effects.

Several papers have reviewed the impact of disruptions on supply chains (Snyder *et al* 2016) and some researchers have sought to categorize disruptions based on certain metrics. To the best of the authors' knowledge, however, there has been limited work to group types of risk based on similarity metrics using clustering-based machine learning methods. The closest study we identify is a 2012 paper in which the authors propose a taxonomy for categorizing risk by reviewing literature on supply chain disruptions for the preceding ten years to organize the literature being reviewed (Monroe *et al* 2012). The novelty in our work comes from clustering actual disruption events as opposed to articles about them. In addition, our clustering framework makes such analysis and comparison more scalable as the number of disruptions and metrics increase. If a company or stakeholder wanted to include new metrics for comparison, this could easily be done with our method.

We believe that grouping disruptions can facilitate more robust mitigation strategies that can be applied across multiple disruption types with positive effects. The goal of this paper is to provide a framework for categorizing different manufacturing sector disruptions by analyzing significant disasters over the past two decades. In addition, we identify disaster responses and recovery and mitigation strategies that support manufacturing infrastructure by developing resilient supply chains. We also highlight the lack of data to effectively include environmental considerations within each disruption category.

1.2. Relevant supply chain and risk definitions

Manufacturing supply chains: a supply chain consists of different entities connected by the physical flow of materials (Shao 2013). In manufacturing supply chains, this usually involves tracking the stakeholders and flows of materials and information for a specific product from the raw materials through manufacturing, consumption, and eventually end of life, and sometimes the opportunity for recycling through further processing.

Supply chain disruptions: events that impede or stop the flows of materials, information, services, or financial resources within and between the organizations of a supply chain involved in producing a good or service. Supply chain disturbances also interrupt normal business operations of the firms in the supply chain (Wagner and Bode 2008).

Supply chain flexibility: a supply chain's ability to accommodate disruptions by changing its course and even the target, leaving the flow itself (the throughput) unaffected (Behzadi *et al* 2020).

Supply chain resilience: the ability to return to normal operations post-disruption (Punter 2013). Resilience can also be described as the supply chain's ability to rapidly and effectively recover from a disruption (Behzadi *et al* 2020).

Supply chain robustness can be qualified as the supply chain network's ability to maintain operations during a crisis (Behzadi *et al* 2020).

Supply chain risk has been defined as an uncertain, negative, unpredictable event that departs from the expected process, function, or performance measure within a supply chain and could lead to adverse outcomes for companies (Wagner and Bode 2008).

Supply chain risk management can be defined as the implementation of strategies to manage risks along the supply chain based on continuous risk assessment, with the objective of reducing vulnerability and ensuring continuity (Wieland and Wallenburg 2012).

1.3. Review of manufacturing supply chain risk methods

Researchers have categorized supply chain risk using various methods and definitions. In Svensson (2002), the author proposed a grouping method based on inbound and outbound vulnerability scenarios. Other researchers have developed supply chain risk categorizations based on impacts. Researchers in Cavinato (2004) group according to risk facing product flows, storage, and inventories. Categories have also been based on probability of disruption and consequences of risk (Sheffi and Rice 2005). Some researchers suggest that supply chain risks should include (a) events with a lower probability but could occur unexpectedly and (b) events that bring substantial negative consequences to the system (Tang 2006a). This study further emphasizes that supply chain risk is managed through coordination or collaboration among the supply chain partners to ensure profitability and continuity. In Goh *et al* (2007) and Kleindorfer and Saad (2005), the authors describe disruption risk which results from natural and man-made disasters (e.g. tsunamis, floods, terrorist attacks, etc). According to Jabbarzadeh *et al* (2016) disruption risk can cause significant economic and social damages.

Our review of methods to investigate and tackle supply chain risk and disruption, presented in table 1, is divided into three subsections: Conceptual Frameworks, Network and Optimization Methods, and Other Methods (e.g. case studies, empirical analysis). When we consider conceptual methods, a number of frameworks have been developed to address risk management in supply chains (Norrman and Lindroth 2004, Craighead *et al* 2007, Moritz 2020). Some researchers break down risk management into five components: drivers, influencers, decision maker characteristics, risk management responses, and performance outcomes (Ritchie and Brindley 2007). The authors in this study advocate for the use of a more diverse set of risk management tools and methodologies to adequately tackle the various issues and contexts around supply chain risk. A recent study by Moritz (2020) identifies nine dimensions of supply chain disruptions for COVID-19. In addition, previous work has been done to develop a framework that supports decision making by assessing the robustness of supply chain networks with different topologies when exposed to disruptive events (Craighead *et al* 2007).

Table 1. A review of methods and tools to improve supply chain under disruptions. The table divides the tools into three categories: conceptual methods (frameworks presenting an idea with little quantitative analysis), network optimization and statistical analysis method and other (which includes general quantitative method, software and literature reviews.

	Method	Tools	References
Conceptual	Conceptual frameworks	Six propositions relating the severity of supply chain disruptions	Craighead *et al* (2007)
		Dimensions of supply chain disruptions for Covid-19, risk breakdown structure (RBS)	Norrman and Lindroth (2004), Moritz (2020)
		Components for risk management: drivers, influencers, decision maker characteristics, risk management responses and performance outcomes.	Ritchie and Brindley (2007)
Network Optimization & Statistical Analysis	General Risk Modeling Tools	Supply risk as the geometric mean of disruption potential, trade exposure, and economic vulnerability	Nassar *et al* (2020)
		Supply chain operations reference (SCOR) model	Ntabe *et al* (2015), Sellitto *et al* (2015)
	Resilience, Robustness and Flexibility	Resilience frameworks for risk management, identify and mitigate ripple effects in supply chain, targeted attacks versus random failures	Cetinkaya *et al* (2013), Kim *et al* (2015), Ivanov (2018), Ojha *et al* (2018), Perera *et al* (2018c), Ivanov and Dolgui (2020)
	Simulations and Network Topology	Time to recovery (TTR) node analysis, demand, supply and lead-time uncertainties analysis, topological network characteristics	Acar *et al* (2010), Kim *et al* (2011), Kito *et al* (2014), Brintrup *et al* (2015), Gang *et al* (2015), Simchi-Levi *et al* (2015), Orenstein (2016), Adenso-Díaz *et al* (2018), Perera *et al* (2018b), Simchi-Levi (2020)
		Bayesian network theory and simulations	Ojha *et al* (2018)
Others	Case Studies and Empirical Quantitative Measures	9 robust supply chain strategies, impact of R&D investing on mitigating disruptions	Tang (2006b), Wagner and Bode (2008), Moritz (2020), Parast (2020)
		Principles of dynamic capabilities theory, failure modes and effects analysis (FEMA), survey Analysis	Wagner and Bode (2008), Bradley (2014), Baghersad and Zobel (2021)
	Supply Chain Mapping Software	Resilinc, Elementum, Razient, and MetricStream	Sheffi (2018)
	Causal Inference and General Equilibrium Models	General equilibrium model of production, Regression and difference in difference equations	Nassar *et al* (2020)
	Review papers	Comprehensive review of literature for modeling the robustness and resilience in supply chain networks	Khan and Burnes (2007), Tukamuhabwa *et al* (2015), Perera *et al* (2018a)
		Review on supply chain risk management and artificial intelligence and global supply chain design	Meixell and Gargeya (2005), Baryannis *et al* (2019)

Several studies use different methods to explore supply chain risk in the context of industrial and manufacturing supply chains, especially using Network Optimization and Statistical Analysis (Kim *et al* 2011, 2015, Cetinkaya *et al* 2013, Kito *et al* 2014, Gang *et al* 2015, Orenstein 2016, Ojha *et al* 2018, Perera *et al* 2018c). A study by Tang and Musa (2011)suggests that supply chain risk is managed through coordination or collaboration among supply chain partners to ensure profitability and continuity. Time to recover has been used in disruption analysis and is defined as the time it would take for a particular node (e.g. supplier facility, distribution center, transportation hub) to be restored to full functionality after a disturbance (Chee and Lee 2014, Simchi-Levi *et al* 2015). Another study uses Bayesian network theory to analyze a multi-echelon network faced with simultaneous interruptions and evaluate the ripple effect of node interruption via metrics like fragility, service level, inventory cost, and lost sales (Ojha *et al* 2018). Other researchers use a simulation based approach to propose a new metric based on the effect on service level of the collapse of active transportation links and understand how different design factors affect robustness (Adenso-Díaz *et al* 2018). Additionally, researchers used a decision support framework for a global manufacturer of specialty chemicals to investigate the relative impact of demand, supply, and lead-time uncertainties on cost and customer service performance (Acar *et al* 2010). The authors of Nassar *et al* (2020) define supply risk as a combination of three factors: the likelihood of a foreign supply disruption, the dependency of manufacturers on foreign supplies, and the ability of manufacturers to withstand a supply disruption.

For more general methods, a recent study by Carvalho *et al* (2021) relies on a general equilibrium model of production networks to estimate the overall macroeconomic impact of the disaster taking propagation effects into account. Additionally, a number of organizations offer technologies that can map an organization's suppliers to identify risk and identify mitigation strategies (Sheffi and Rice 2005).

2. Materials and methods

We reviewed 20 years' worth of supply chain disruptions in the United States using data obtained from a database consisting of worldwide natural and technology disaster data since 1900, supplemented by a literature review. After filtering our data set by location, credibility, and for duplicates, we obtain 90 distinct documented interruptions. We identify key metrics obtained from our literature review for supply chain disruption, including Duration, Likelihood of Disruption, Warning Capability, and Position of Disruption.

2.1. Metrics characterizing disruption

Duration refers to how long the disruption lasts and is generally captured as a continuous variable representing the number of time periods (hours, days, etc) over which the disruption happened. We focus on whether the disruption was acute (days to weeks) or chronic (months to years), and we use a binary variable to represent these two states.

The Likelihood of Disruption metric describes the probability of a disruption occurring in a given location and/or time period. Supply chains are vulnerable to risks resulting from demand and supply coordination (Kleindorfer and Saad 2005) which are usually high-likelihood and low-impact risks (Sheffi and Rice 2005) and also high-impact, low-likelihood risks (e.g. microchip shortage) that majorly impact organizations (Chopra and Sodhi 2004, Kleindorfer and Saad 2005). A prolific tool in the literature is the probability vs. severity matrix in Norrman and Jansson (2004) which evaluates risks based on the probability of an occurrence and the severity of the impact. It is challenging to compute or even estimate a probability distribution for all disturbances that occur even in a small sub-region of the United States. This problem is quite complex because there are many kinds of disruptions, each with their own causes and underlying distribution. In this analysis, we focus mainly on whether the disruption is a rare event (e.g. Japan's 2011 compound disaster) or reoccurs (e.g. hurricanes), which simplifies our variable.

Warning Capability consists of the interactions and coordination of supply chain resources to detect a pending or realized disruption and to subsequently disseminate pertinent information about the disruption to relevant entities within the supply chain (Craighead *et al* 2007). The authors argue that Warning Capability allows visibility into events such as the 2002 West Coast ports strike that take some time to become disruptive. In our analysis, we focus on whether stakeholders can receive warning at least two days prior to the interruption. We hypothesize that any warning less than that may provide insufficient time for any potential mitigation, such as moving populations or planning around disruption. We do this to create a binary variable that states whether a warning occurred and settles on the assumption that a warning of less than two days can also be considered as no warning. Our Warning Capability variable takes on the values 'yes' or 'none,' the former denoting the availability of a warning and the latter representing little or no warning capability.

Another factor we consider is the Position of Disruption occurrence in the supply chain. Supply chains can be divided into tiers, each tier representing different production stages and arranged such that the outputs from one tier are the inputs to the next (Craighead *et al* 2007). To characterize a disruption, it is essential to understand whether interruptions are more localized (i.e. occur in a single tier) or multi-tiered and as such occurred within multiple tiers of the supply chain. We therefore consider two positions: Single-tiered (e.g. upstream supplier, distribution etc) or Multi-tiered.

2.2. Disaster data extraction and analysis

We study historical disruptions to U.S. manufacturing supply chains since 2000 obtained from the Emergency Events Database (EM-DAT) database, which was created by the CRED at University of Leuven,

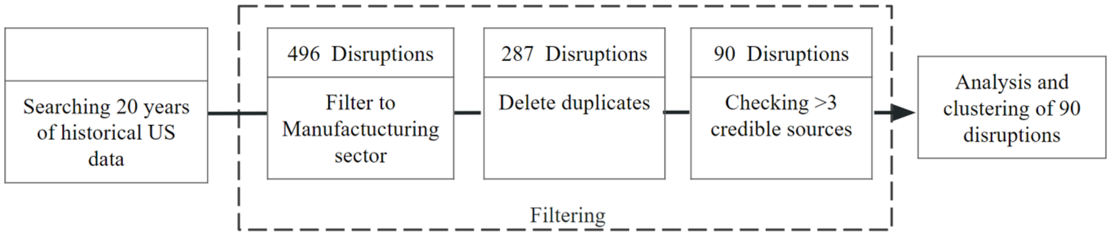

Figure 1. Overview of process for selecting disruptions—sourcing, filtering and analysis.

Belgium and covers natural and technological disasters and their effects from 1900 to the present (Guha-Sapir *et al* 2009). This preliminary data set contained 496 events. We filter this data set to include data starting from 2000 and occurring in the United States. We supplement this data set by researching news articles on events in the U.S. within our desired timeframe.

We then filter our data to include only those events that directly affected manufacturing supply chains and were reported by more than three credible sources, such as recognized media companies and journal publications, ensuring that we select disruptions using accurate information about their impacts and occurrence. The manufacturing sector was defined according to the North American Industry Classification System, which delineates the industry within categories 31–33. Our selection process resulted in 90 events detailed in table 3 located in the appendix, which underlies all of our analysis.

Using the metrics defined above, we create a five-dimensional binary axis on which we place our study's disruptions. Focusing on well documented events allows us to create labels for our five metrics using recorded information about each disruption studied. We create a table with five columns for each metric, with every row representing a particular disruption. As previously mentioned, all five metrics take on binary values to simplify our analysis. In figure 1, we present the full pipeline for selecting disruptions which were used during our analysis.

2.3. Framework for categorizing disruptions

We use agglomerative hierarchical clustering, an unsupervised clustering algorithm, to group the different disruptions according to our five metrics. This method focuses on creating clusters that are predominantly ordered from top to bottom. Every data observation (i.e. disaster) is initialized in its own cluster, and then pairs of clusters are merged based on similarity as one moves up the hierarchy. The core of the hierarchical clustering method relies on the construction and analysis of the dendrogram, a tree diagram that reflects the hierarchical relationships between different sets of data. The vertical axis of the dendrogram represents the distance between clusters using some predefined metrics such as Euclidean distance. The clusters break down into smaller and smaller units as we move from top to bottom of the dendrogram until we obtain clusters with single data points.

The hierarchical clustering method is used because no assumption is made about the number of clusters while constructing the dendrogram. To deduce the number of clusters, the dendrogram is sliced through horizontally, creating a cutoff threshold. The number of clusters then equals the number of branches that our horizontal threshold cuts across. It is important to note that although a set of clusters is generated via the horizontal cutoff line, the decision maker using the framework can still access information about all possible cluster groupings, and thus can increase or decrease the granularity of clustering by changing the threshold line. The location of the horizontal threshold is usually decided visually (by looking at the distances between clusters) or by relying on domain knowledge around a given problem. The proposed framework, denoted by figure 2, characterizes historical interruptions according to the metrics above and allows decision makers to obtain tailored recommendations by categorizing disruptions into a specific group. The process for selecting the number of clusters for this analysis is discussed in the next section.

3. Results

The dendrogram in figure 3 denotes the hierarchical relationship between the events in our data and allows us to visualize how best to put different disturbances into groups. The distance (Euclidian) between data points represents dissimilarities, and the height of the blocks represents the distance between clusters. The horizontal line is a threshold selected by the decision maker which allows them to choose the number of clusters. In our analysis, we relied mainly on a combination of visual inspection of the dendrogram and domain knowledge to select the correct number of clusters. First, we selected highly dissimilar clusters

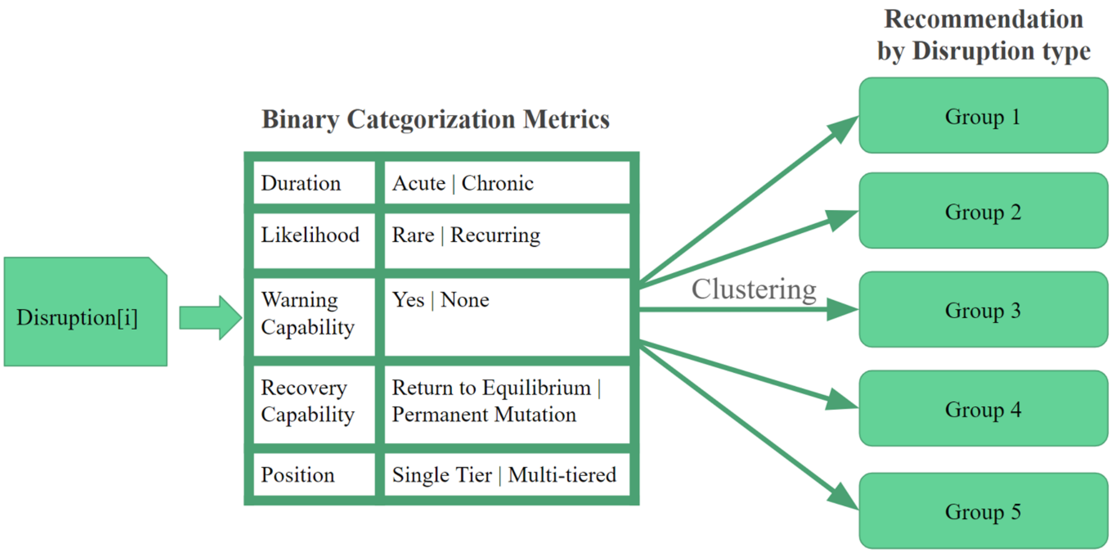

Figure 2. Framework for categorizing disruptions that involves identifying the categorization metrics for each disruption and using these metrics to place the disruption in one of five groups generated via hierarchical clustering (discussed in the Methods section). Based on the selected disruptions groups, risk mitigation strategies and recommendations are developed.

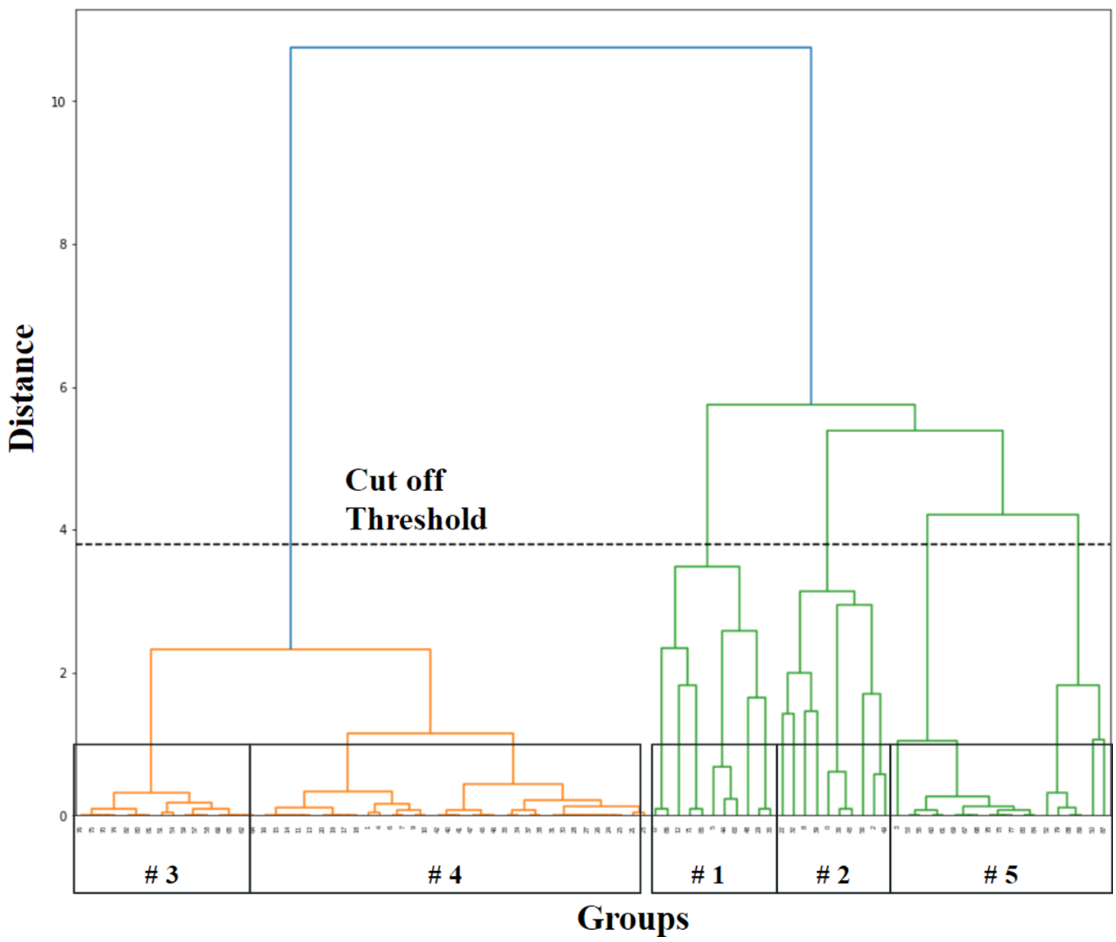

Figure 3. Dendrogram denoting the five disruption clusters and the selected cut-off threshold indicated by the black dotted line which enables the creation of five clusters. The height of the dendrogram represents the distance between clusters. Observing the dendrogram from the top to bottom, we note that the big difference between clusters is between the components of the green cluster (Groups 1, 2 and 5) versus the orange cluster (Groups 3 and 4) as the vertical height (blue line) is longer for the former. In addition, our figure reflects relative proximity (similarity) of our different groups. For instance, the dendrogram suggests that Group 5 is much more similar to Group 4 than it is to Group 2.

Table 2. Five disruption groups identified and their corresponding characteristics based on the defined metrics: duration, likelihood of disruption, warning capability and position of disruption.

Group	Name	Characteristics	Key recommendations	Real world examples
Group 1	Rare Events with Warning	Rare, Warning Capability Present	Develop technologies promoting permanently localizing Fraction of Supply Chain (Sarkis *et al* 2020, Zhu *et al* 2020)	COVID-19 Pandemic—Goods Shortage, 2012 West Coast ports lockout (Automotive, manufacturing, transport delay)
Group 2	Localised Disturbances	Acute, No Warning, Single tier	Sourcing from local substitutes (Remko 2020) Detection of disruptions, supply chain design, and deployment of contingency plans (Jacobides *et al* 2016)	2012 Evonik Chemical Plant Fire, 2000 fire at Phillips microchip plant, 2007 Toy recalls due to lead poisoning
Group 3	Recurring Targeted Attacks	Acute, Recurring, No Warning, Multi-tiered	Invest in educating employees with best practices regarding cyber security attacks Develop a response plan to a cyber attack Implement novel technologies (e.g. block chain) to better secure their data	2021 Colonial Pipeline cyber attack, 2019 Cyber attack on Natural Gas compressor station
Group 4	Recurring Natural Disasters	Acute, Reoccurring, Yes Warning, Multi-tiered	Build state and local capacity for recovery (Sutton and Tierney 2006) Geographically separated primary and backup suppliers (Chopra and Sodhi 2004)	2005 Hurricane Katrina, 2012 Hurricane Sandy
Group 5	Rare Targeted Attacks	Acute, Rare, Multi-tiered	Understanding the historical and current political climates of the supplier geographic origin Risk mitigation strategies that balance recurrent risks and cost savings and disruptive risks and costs (Chopra and Sodhi 2014)	2001 9/11 terrorist attack, 2018 Camp Fire

containing more than one data point and having large separation distances. This allowed us to limit our threshold values to a range between 2.5 and 8. At the same time, we also wanted a small set of clusters bearing distinctive, easily recognized features. The latter step was carried out by testing different thresholds in our desired range, observing the specific examples that fell into each bucket, and then selecting the number of clusters having specific characteristics that were easily identified and explained. We settled on a threshold value of 3.8 that generated five clusters as denoted by table 2. In addition, we ran the clustering algorithm multiple times and observed that the clusters remained relatively consistent between runs.

One limitation of our modeling is that we generally lack data and visibility into some impacts of disruptions, especially around socio-environmental factors. As a result, our model does not include metrics quantifying the environmental cost of disruptions. These are absent because they are not easily quantifiable and have historically not been properly estimated in the literature. However, the clustering framework is flexible and could allow such metrics to be included in the future. In addition, when creating the groupings, our model assumes that all metrics are weighted equally. This is not always the case in reality, as it depends on the priorities of the company or decision makers, and this aspect of the model could be adjusted in the future.

4. Mitigation strategies for disruption groups

The mitigation of process and demand risk has a direct effect on supply chain performance (Chen *et al* 2013). From our clustering analysis, we identify five groups with distinctive characteristics and thus require targeted economic and environmental mitigation strategies. We propose mitigation strategies identified from the literature and also specify approaches for each of the five disruption groups presented in table 2. While the strategies are not exhaustive, they provide an initial guide for actions we believe could be beneficial to disruptions at the group level. In addition to using the framework as a standalone tool, policy makers and other stakeholders can leverage our data to characterize new disruptions and apply our model to group disruptions and discover appropriate mitigation strategies.

4.1. Group 1—rare events with warning

This disruption group is characterized by events that occur rarely but usually have some warning capability. This group tends to capture events such as labor strikes, goods shortages, and trade wars. The 2012 West Coast ports lockout, which impacted a number of manufacturing sectors, and the current shortage in various manufactured goods due to the COVID-19 pandemic are good examples of this group. The following approaches are recommended for this disruption category:

Developing a risk mitigation strategy that balances recurrent risks and cost savings (i.e. centralizing resources, pooling, standardization of parts) and disruptive risks and costs (i.e. decentralization, multiple suppliers, limited common parts) (Bradley 2014). Additionally, conducting risk analysis at all operational levels, from suppliers to customers. This could include scenario planning around various types of risk using tools such as the tabletop stress test exercise. This method has been used to investigate how employers and the company react under pressure to planned or unplanned events (Fruhlinger 2021).

Another method for balancing risk involves developing the technologies and tools that promote local sourcing of production and permanently localizing a fraction of the manufacturing supply chain network (Sarkis *et al* 2020, Zhu *et al* 2020). Identifying the sources of disruptive risk and attributing a hard cost to each disruptive risk versus the probability of a disruption can be an effective method to break down risk planning (Chopra and Sodhi 2004).

4.2. Group 2—localized disruptions

Localized disruptions, as their name suggests, tend to occur within a single tier of the supply chain. These usually happen over a relatively short period with little or no warning and can include events like factory accidents, transportation failures, and delays. The 2012 Evonik chemical plant fire (Reisch 2012), and the 2000 fire at the Phillips microchip plant (Eglin 2003) are examples of disruption that fall into this group. The following are recommendations for localized disruptions.

Outsourcing a portion of production and supplier integration can mitigate the effects of single-location 'super suppliers', which emerge from the merging of many smaller suppliers especially during economic downturns. These 'super suppliers' capture a large portion of demand and can put an entire industry (e.g. semiconductors) at risk if they fail. This process is efficient for the detection of disruptions, supply chain design, and deployment of contingency plans (Jacobides *et al* 2016).

Sourcing from local substitutes (Remko 2020) and supply chain segmentation and supply chain segmentation can greatly reduce impacts of disruptions when practices such as duplicating manufacturing capabilities at multiple facilities and locating distribution centers closer to consumers for high demand products are employed (Chopra and Sodhi 2014).

4.3. Group 3—recurrent targeted attacks

These events occur without warning over a relatively short period of time and can affect multiple supply chain tiers. They can also be recurring in nature and are generally man-made. The bulk of recurrent targeted attacks are related to cybersecurity breaches, including the 2021 Colonial pipeline cyberattack, the 2019 cyberattack on a natural gas compressor station, and the 2021 JBS meat processing cyberattack. The following recommendations are proposed for this disruption group:

Educate employees on best practices regarding cybersecurity attacks. In addition, decision makers should implement novel technologies such as block chain and homomorphic encryption which allows users to work with encrypted data without first decrypting to better secure their data (Boehm *et al* 2022).

More so, we suggest the adoption of risk mitigation approaches that balance recurrent risks and cost savings (e,g., centralizing resources, pooling, standardization of parts) and disruptive risks and costs (e.g. decentralization, multiple suppliers, limited common parts) (Chopra and Sodhi 2014). More so, organizations should focus on creating multiple layers of defense strategies (e.g. at level of quality control, equipment control, decision making, worker fundamental behaviors, emergency preparedness, etc) against unknown risks (Chester and Horvath 2009).

4.4. Group 4—natural disasters

This disaster group consists of recurring natural disasters with reasonable warning. A few examples of events in this group include the 2005 Hurricane Katrina that created significant damage to the U.S. Gulf Coast and 2012 Hurricane Sandy, one of the deadliest and most destructive storms that affected 24 U.S. states (Gabe *et al* 2005, Kunz *et al* 2013). As such, the following recommendations centered around maintaining systems and infrastructure supporting disaster preparedness are suggested:

Countries should be encouraged to build state and local capacity for recovery. This can be done by allocating resources to disaster preparedness training and by updating and maintaining disaster resistant infrastructure to make regions more resilient (Sutton and Tierney 2006).

Companies should develop an optimized and organized distribution network that can react quickly to change (Charles *et al* 2010). This can be done via improved oversight of regulatory institutions (e.g. for quality, disaster preparedness, etc) and frequent monitoring and updating of disaster prevention technologies and resources. To prevent a single natural disaster from shutting down all supply chains, companies should select primary and backup suppliers from different geographies and create alternate distribution networks (Chopra and Sodhi 2004).

Natural disasters are very connected to climate and environment. As such, planning around existing environmental risks and impacts is essential. Investing in predictive technologies for recurring risks such as wildfires on the West Coast allows supply chain decision makers to develop contingency plans to reduce prospective economic and environmental impacts (Blume 2021).

4.5. Group 5—rare attacks

This group is characterized by rare events (low probability with high impact) that occur with no warning and are generally caused by man-made or targeted attacks but also by natural events. Some examples include the 2001 9/11 terrorist attack. For this category, we recommend the following mitigation strategies:

Understanding the historical and current political climates of areas where suppliers are located and developing a viable contingency plan for worst-case scenarios . It is especially critical that manufacturing stakeholders build multi-layered mitigation strategies to defend against unknown risks (Chester and Horvath 2009).

Having primary and backup suppliers that are geographically separated and developing alternate distribution networks is recommended (Remko 2020).

4.6. General mitigation strategies

In this section, we highlight the following general risk mitigation strategies that are applicable across all of the five groups:

Overestimating risk. Underestimating disruptive risk can be more costly than overestimating it (Chopra and Sodhi 2014). Analyses around impacts of disruptions consistently underestimate risk by focusing solely on economic costs. Adding potential environmental costs such as increased emissions or proper waste management expenses can lead to more accurate risk forecasts. Quantifying environmental effects such as water usage (Horvath *et al* 1995), generation of waste water, and toxic emissions (Boughton and Horvath 2006) can provide more realistic cost accounting methods for risk.

Supply chain due diligence. This involves a constant process of investigating and vetting supply chain partners before and during contracted periods based on monitoring parameters that accurately capture potential risks (Sindik and Jimenez 2021). In addition, company managers should invest in monitoring technologies that can allow better warning capability early enough to allow for the implementation of a planned response to disruption (Mani *et al* 2017).

Alternative transportation investments. Transportation is a significant source of global carbon emissions, and transport delays or interruptions can lead to higher emissions. Investments in alternative transportation technology and infrastructure (e.g. vehicle electrification, hydrogen fuel) can reduce overall air pollution as well as emissions impacts of supply chain disruptions. Governing bodies should enact policies encouraging companies to invest in eco-friendly technologies such as electric vehicles to further reduce emissions (Yu *et al* 2021).

Adding inventory. This is an easy way to build redundancy into supply chains and reduce impacts of disruption (Snyder *et al* 2016). Supply chain decision makers should be encouraged to build up risk mitigation inventory (RMI) and reserve capacity (Tomlin 2006). In the event of disruptions, organizations can use RMI to meet customer demand (Simchi-Levi *et al* 2014, Lücker *et al* 2019).

5. Environmental costs of disruptions and limitations

The environmental impacts and costs of disturbances are usually disregarded when developing models for resilient supply chains (Fahimnia and Jabbarzadeh 2016). Our proposed method aims to support medium- and long-term planning by combining disruptions into a small set of groups, enabling planners to design targeted mitigation strategies at the group level. Currently, the groups generated by our method include mainly information around the nature and characteristics of disruptions. However, there is insufficient data as of today to include environmental impacts of disruptions.

Environmental costs of supply chain disruptions can result from a number of factors including natural disasters (hurricanes, floods etc) (Waters 2011), industrial accidents such as fires and explosions (Giannakis and Papadopoulos 2016) and activities that result in generation of hazardous materials (Dües *et al* 2013). Further, modern manufacturing methods usually involve extensive use of various hazardous chemicals in different manufacturing steps. Some manufacturing sectors (e.g. iron and steel industry) receive attention for their high intensity of materials consumption (Dai 2015), energy consumption (Sun *et al* 2018), CO2 emission and particulate matter emission (Li *et al* 2019). While there is an increased interest in developing more sustainable supply chains, the integration of environmental factors into the supply chains is still very challenging (Su *et al* 2016, Reefke and Sundaram 2017). In addition, studies that do incorporate sustainability into their manufacturing supply chain risk analysis tend to focus on a limited set of environmental factors, such as carbon emissions (Chaabane *et al* 2011, Fahimnia *et al* 2018) and inventory wastage (Fahimnia *et al* 2017). While important, this is just a subset of factors that should be considered. For instance, there is also environmental risk associated with a disaster that damages containment systems or results in the unintended release of gases or chemicals, as was the case with Houston's Arkema chemical plant during Hurricane Harvey in 2017. Another example is the environmental impact of having a nuclear plant's cooling systems stop functioning, as in the 2011 Fukushima disaster. More effort must therefore be made to properly measure, document, and estimate the various environmental effects of disruptions.

With environmental risks such as climate change, deforestation, and water insecurity representing $1.26 trillion in projected financial impact over the next five years, according to the Carbon Disclosure Project, the inability of existing models to properly account for environmental risks should be cause for widespread alarm. Some of these costs are projected to be passed down the supply chain, with the highest price increases expected in manufacturing ($64 billion), energy generation ($11 billion) and food, beverage and agriculture ($17 billion) sustaining the highest potential increases in price (CDP Global 2021). A limited number of studies have sought to tackle this issue by incorporating sustainability measures into their supply chain risk analysis. The authors in Jones *et al* (2009) measure the socioeconomic and environmental consequences of failure in manufacturing systems using a risk-based technique known as delay-time analysis (DTA). DTA establishes a maintenance strategy by estimating the time between an initial failure signal and actual failure, and has been applied to several areas in the manufacturing industry (Christer *et al* 2000). In Jones *et al* (2009), researchers implement DTA by using the probability of failure to estimate the down time of the process, and then multiplying the desired impact (e.g. environmental, economic) per period by the estimated down time.

In Jabbarzadeh *et al* (2018), the authors develop a hybrid method that establishes outsourcing decisions and resilience strategies that minimize the expected total cost of the disruption and maximize the overall sustainability performance during disruptions. Another study proposes a multi-objective location allocation model for designing a sustainable and resilient pharmaceutical supply chain network (Zahiri *et al* 2017). In addition, in Fahimnia and Jabbarzadeh (2016), authors study the interactions between sustainability and resilience relationship at the supply chain design level by finding trade-off solutions for developing a resilient and sustainable supply chain using a multi-objective optimization model that relies on sustainability performance scoring. More so, most supply chains require multi-modal transport which refers to using more than one mode in a transport chain (e.g. road, air, rail and water) (Monios and Bergqvist 2017). These different modes of transportation have carbon footprints that significantly impacts the environment. According to Grampella *et al* (2017), a 1% rise in air traffic movements can cause the total environmental effects (noise and air pollution) due to airports levels to increase by 1.05%. Different supply chains interruptions can result in transport delays and bottlenecks that can create significant increases to the already high emissions from transportation systems.

Techniques such as the Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts and Risk-Screening Environmental Indicators are used to quantify geographic and chemical environmental impacts in the United States (Lam *et al* 2011). As data becomes available around environmental factors, these tools and impacts can be incorporated into the clustering model, so as to create grouping that include environmental impacts. For instance, with appropriate amount and type of data, new metrics could be defined around environmental effects (e.g. number of people affected, intensity of environmental impacts, etc). These metrics could then be added into our model to develop more meaningful groupings that are also characterized by their environmental impacts.

6. Conclusion

In the recent decades, manufacturing supply chains have become increasingly exposed to a large number and variety of disruptions. It is thus important to understand and even group these different disturbances based on stakeholder-provided metrics to support planning processes that promote adaptable, resilient manufacturing supply chains.In this paper, we review disruptions to U.S. manufacturing supply chains from the past two decades and propose a method for categorizing any given disruption using metrics identified from the literature. The methodology informs strategic disruption mitigation planning as it allows companies to cluster identified disruptions based on stakeholder interests. Consolidating disruptions into a smaller and more manageable set of groups can allow planners to effectively develop and implement mitigation strategies at the group level. In the paper, we discuss mitigation strategies by group level to demonstrate strategies that have been adopted in the literature to mitigate disruption effects.

The model in this study is flexible and can be used across different sectors. Similarly, the metrics are general and can be used for analyzing disruptions to different kinds of supply chains. Decision makers and companies using this model have the ability to define and add more specific metrics. A limitation to our model is that we are unable to include environmental impacts of supply chain disruptions, as they remain difficult to measure and are thus usually excluded in disruption cost accounting. We conclude the paper with some suggestions on how our model can incorporate environmental impacts in the future. From analysis, disruptions can be placed into five distinct categories, and we provide mitigation strategies to address impacts for each. We also provide mitigation strategies for potential environmental impacts, but these are quite limited.

Through this work, in the long term, stakeholders and decision makers at various stages of manufacturing systems can shift away from reactive responses to catastrophic events—which can create high emissions, water use, and other negative environmental impacts—and shift toward proactive intervention strategies that include environmental considerations. We would like to conduct a similar analysis using disruptions to different sectors across different regions, as our initial analysis focused on the United States.

Data availability statement

The data that support the findings of this study are openly available and found within the article in table 3 in the appendix. All data that support the findings of this study are included within the article (and any supplementary information files).

Acknowledgments

This work was co-authored by Lawrence Berkeley National Laboratory under Contract No. DE-AC02-05CH11231 and by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the Office of Energy Efficiency and Renewable Energy (EERE) Advanced Manufacturing Office (AMO). The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

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Conflict of interest

The authors report there are no competing interests to declare.

Appendix

Table 3. Selected disruptions to the United States with values along the five characteristic metrics.

Year	Disruption	Duration	Likelihood	Warning capability	Disruption position
2000	Fire at the Philips microchip plant	Acute	Rare	No	Single tier
2000	Tropical cyclone—Leslie	Acute	Reoccurring	Yes	Multi-tiered
2001	Land Rover lay-off	Acute	Rare	No	Single tier
2001	9/11 terrorist attack	Acute	Rare	No	Multi-tiered
2001	Tropical cyclone—Allison	Acute	Reoccurring	Yes	Multi-tiered
2002	West Coast ports lockout	Acute	Rare	Yes	Multi-tiered
2002	Tropical cyclone—Lili	Acute	Reoccurring	Yes	Multi-tiered
2002	Tropical cyclone—Isidore	Acute	Reoccurring	Yes	Multi-tiered
2003	Bird Flu	Chronic	Rare	No	Multi-tiered
2003	Tropical cyclone—Isabel	Acute	Reoccurring	Yes	Multi-tiered
2003	Tropical cyclone—Bill	Acute	Reoccurring	Yes	Multi-tiered
2004	Hurricane Jeanne	Acute	Reoccurring	Yes	Multi-tiered
2004	Influenza vaccine shortage	Chronic	Rare	Yes	Single tier
2004	Tropical cyclone Frances	Acute	Reoccurring	Yes	Multi-tiered
2004	Tropical cyclone Gaston	Acute	Reoccurring	Yes	Multi-tiered
2004	Tropical cyclone Charley	Acute	Reoccurring	Yes	Multi-tiered
2004	Tropical cyclone Jeanne	Acute	Reoccurring	Yes	Multi-tiered
2005	Hurricanne Katrina	Acute	Reoccurring	Yes	Multi-tiered
2005	Hurricane 'Wilma'	Acute	Reoccurring	Yes	Multi-tiered
2005	Tropical cyclone Rita	Acute	Reoccurring	Yes	Multi-tiered
2005	Hurricane 'Dennis'	Acute	Reoccurring	Yes	Multi-tiered
2006	Tropical cyclone Ernesto	Acute	Reoccurring	Yes	Multi-tiered
2007	Toy recalls due to lead poisoning	Chronic	Rare	No	Single tier
2007	Tropical cyclone Erin	Acute	Reoccurring	Yes	Multi-tiered
2008	Hurricane Gustav	Acute	Reoccurring	Yes	Multi-tiered
2008	Hurricane Ike	Acute	Reoccurring	Yes	Multi-tiered
2008	Hurricane Dolly	Acute	Reoccurring	Yes	Multi-tiered
2008	Tropical storm Fay	Acute	Reoccurring	Yes	Multi-tiered
2008	Hurrican Ike	Acute	Reoccurring	Yes	Multi-tiered
2008	Severe winter conditions	Acute	Rare	Yes	Multi-tiered
2008	Hurricane 'Gustav'	Acute	Reoccurring	Yes	Multi-tiered
2008	Hurricane Hanna	Acute	Reoccurring	Yes	Multi-tiered
2009	Toyota Motor Corp. Recalls	Chronic	Rare	No	Single tier
2009	Hurricane 'Ida'	Acute	Reoccurring	Yes	Multi-tiered
2009	Hurricane Bill	Acute	Reoccurring	Yes	Multi-tiered
2010	Iceland Volcano	Acute	Rare	Yes	Multi-tiered
2010	Gulf Oil spill	Acute	Rare	No	Single tier
2010	Hurricane Earl	Acute	Reoccurring	Yes	Multi-tiered
2010	Tropical storm Hermine	Acute	Reoccurring	Yes	Multi-tiered
2011	Great East Japan Earthquake, Tsunami, and Nuclear Accident	Chronic	Rare	No	Multi-tiered
2011	Thailand Floods	Acute	Reoccurring	Yes	Multi-tiered
2011	Hurricane Irene	Acute	Reoccurring	Yes	Multi-tiered
2011	Tropical Storm Lee	Acute	Reoccurring	Yes	Multi-tiered
2012	Evonik Chemical Plant Fire	Acute	Rare	No	Single tier
2012	Port Strikes	Acute	Rare	Yes	Multi-tiered
2012	Hurricane Sandy	Acute	Reoccurring	Yes	Multi-tiered
2012	Hurricane Isaac	Acute	Reoccurring	Yes	Multi-tiered
2012	Tropical storm Debby	Acute	Reoccurring	Yes	Multi-tiered
2012	Waldo Canyon Fire	Acute	Rare	No	Multi-tiered
2013	Target cyber attack	Acute	Rare	No	Single tier
2014	Chemical Spill at Intel Plant	Acute	Reoccurring	No	Single tier
2014	Hurricane Iselle	Acute	Reoccurring	Yes	Multi-tiered
2015	Explosion at China's port city of L Tanjin	Acute	Reoccurring	No	Multi-tiered
2015	Valley Fire	Acute	Rare	No	Multi-tiered

(Continued.)

Table 3. (Continued.)

Year	Disruption	Duration	Likelihood	Warning capability	Disruption position
2015	Tropical cyclone Joaquin	Acute	Reoccurring	Yes	Multi-tiered
2015	Butte Fire	Acute	Rare	No	Multi-tiered
2016	Attack on Water Utility Chemical Controls	Acute	Rare	No	Single tier
2016	Hurricane Hermine	Acute	Reoccurring	Yes	Multi-tiered
2016	Storm Jonas (Snowzilla)	Acute	Reoccurring	Yes	Multi-tiered
2016	Hurricane Matthew	Acute	Reoccurring	Yes	Multi-tiered
2016	Sand Fire	Acute	Rare	No	Multi-tiered
2016	Clayton Fire	Acute	Rare	No	Multi-tiered
2017	Hurricane Maria	Acute	Reoccurring	Yes	Multi-tiered
2017	Hurricane Harvey	Acute	Rare	Yes	Multi-tiered
2017	Hurricane 'Irma'	Acute	Reoccurring	Yes	Multi-tiered
2017	Hurricane 'Maria'	Acute	Reoccurring	Yes	Multi-tiered
2017	Hurricane 'Nate'	Acute	Reoccurring	Yes	Multi-tiered
2017	Wall Fire, Alamo Fire, Whittier Fire	Acute	Rare	No	Multi-tiered
2017	Tubbs, Atlas, Nuns Fires	Acute	Rare	No	Multi-tiered
2017	Thomas' Wildfire	Acute	Rare	No	Multi-tiered
2018	Hurricane Florence	Acute	Reoccurring	Yes	Multi-tiered
2018	US-China Trade conflicts	Chronic	Rare	Yes	Multi-tiered
2018	Kilauea Lava flow	Chronic	Rare	Yes	Multi-tiered
2018	Carr and Mendocino Complex fires	Acute	Rare	No	Multi-tiered
2018	Hurricane Florence	Acute	Reoccurring	Yes	Multi-tiered
2018	Hurricane Michael	Acute	Reoccurring	Yes	Multi-tiered
2018	Tropical storm 'Alberto'	Acute	Reoccurring	Yes	Multi-tiered
2018	Camp Fire	Acute	Rare	No	Multi-tiered
2018	Woolsey Fire	Acute	Rare	No	Multi-tiered
2019	Cyber attack on Natural Gas compressor station	Acute	Reoccurring	No	Multi-tiered
2019	Tropical storm 'Imelda'	Acute	Reoccurring	Yes	Multi-tiered
2019	Tropical cylone 'Barry'	Acute	Reoccurring	Yes	Multi-tiered
2019	Tropical cyclone 'Dorian'	Acute	Reoccurring	Yes	Multi-tiered
2019	Saddleridge fire & Sandalwood fire	Acute	Rare	No	Multi-tiered
2019	Kincade Fire	Acute	Rare	No	Multi-tiered
2020	COVID-19—Good shortage	Chronic	Rare	Yes	Multi-tiered
2020	U.S.-China Trade War	Chronic	Rare	Yes	Multi-tiered
2021	Energy Cyber Attack	Acute	Reoccurring	No	
2021	Colonial Pipeline cyber attack	Acute	Reoccurring	No	Multi-tiered
2021	JBS meat processing cyber attack	Acute	Reoccurring	No	Multi-tiered

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