DISTRUPTIONS IN SUPPLY CHAIN: AN AGENT-BASED MODEL SIMULATION TO MEASURE RESILIENCY AND PERFORMANCE DURING DISASTERS

by

Laura Lynn Brewer

A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Business Administration

Charlotte

2023

Approved by:

____
Dr. Moutaz Khouja

____
Dr. Chandra Subramanian

____
Dr. Reginald Silver

____
Dr. Franz Kellermanns

ABSTRACT

Laura L Brewer. Disruptions In Supply Chain: An Agent-Based Model Simulation To Measure Resiliency And Performance During Disasters

(Under the direction of Dr. Moutaz Khouja)

Supply chain disruptions have been a major concern in businesses and society. Our goal is to study these disruptions and analyze ways to mitigate their effects. To do so, we propose an agent-based model simulation. In our model, we consider the following: the supply chain is generic in structure; however, we will focus on three types of supply chains, customer focused, low cost, and dual-purpose supply chains. The supply chain has a varying degree of connectivity between echelons. Disruptions will include repeatable small-scale events and non-repeatable large events. The managerial decisions considered include excess capacity, the amount of safety stock at each echelon of the supply chain, the geographical dispersion of partners, and the number of first and second tier suppliers. To measure the resiliency in our simulation, we will compute the service levels, the time needed to return to normal operations, profit, and lead time.

ACKNOWLEDGEMENTS

Many thanks to my chair, Dr. Moutaz Khouja for having patience and understanding that is equivalent to a saint and for being a wonderful teacher through this process. I am eternally grateful. I have greatly benefited from your knowledge, and I hope you will teach me more. Thank you to my committee, Dr. Chandra Subramaniam, Dr. Reginald Silver, and Dr. Franz Kellermanns for your efforts and contributions to this work. Thank you to Ted Carmichael for your knowledge and patience.

DEDICATION

For my mom, my best friend, who taught me strength, determination, and resilience. Mom, you are my rock! For my husband, who was there through every tear, every challenge, every victory, every moment of chaos, and whom I love dearly. For my stepdaughters, I pray they always know their worth and know how much I love them. For my friends, who can see me on a regular basis again after my twelve-year academic hiatus but who understood why. For my mentors, Dr. Medlin, Dr. Vannoy, Dr. Dave, and the countless others who've helped anytime I asked. For my brother and granny, I know ya'll can see me from up there. For every cancer survivor who has risen above and decided that cancer will not take over their life, but instead, taught us how to live. And lastly, to my Lord, my savior, I am blessed more than I deserve.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

A few years ago, the words "supply chain" were hardly ever heard of and now, the daily news communicates what item is lacking in supply this week due to "supply chain problems". From asking why toilet paper was scarce, to wondering why baby food was hard to find, supply chains have come to the forefront of the economy and have affected everyone in their everyday life. When we think of a supply chain, we think of all the buyers, sellers, and operational functions that are spread across the chain. These entities can be global in nature, or the entities can be domestic, but the biggest feature of a supply chain is that it can consist of a few businesses or hundreds of entities. Either way, someone must manage the supply chain, especially when the supply chain has disruptions, such as the recent pandemic that has sent most supply chains into a panic.

There are several definitions of supply chains in the literature (Mentzer, et al., 2011). The essential elements of the definitions are that a supply chain is a network of organizations that are connected through material, information, and capital flow with the goal of delivering goods and services to the customer. Supply chains can differ from industry to industry and from product to product as there are many different structures of supply chains. Often, a supply chain will have multiple tiers, multiple players, with different information flows, product flows and different configurations. Decisions on configurations can include raw material purchase locations, transportation options, manufacturing capabilities, and future business needs (Graves and Willems, 2005).

Supply chains can follow different strategies. A supply chain can focus on low costs. An example of this type of supply chain would be big box stores, such as Wal-Mart, that have strong bargaining power with its suppliers. Low-cost supply chains have low inventories, and quick turnaround (Parmigiani, et al., 2011). Low-cost supply chains also tend to have manufacturing that is very agile and the switch from one product to another is quick. Another example of this supply chain is Aldi, a low-cost grocery chain. Some supply chains focus on the consumer and the consumer's specific needs, and we refer to this type of supply chain as a consumer-focused supply chain. The business that has this type of supply chain model will have large safety stock, flexibility to quickly respond to consumers' needs, and requires a higher level of integration between supply chain partners (Korpela, et al., 2001). An example of a customer-based supply chain would be The Fresh Market, a high-end grocery chain. Lastly, a supply chain may have a dual focus on both low-cost and customers, e.g. Harris Teeter. This study will have a dual focus of the above-mentioned types of supply chains, a low-cost efficiency focused supply chain, a customer-oriented supply chain, and thus, a dual customer-cost oriented supply chain.

Supply chains can be multi-tiered and contain hundreds of players or can be simple with only a few players. The trend where companies own the players of their own supply chain is not as popular as it once was (Mena, et al., 2013). Outsourcing different processes to make a product has resulted in many complex supply chains; however, the complexity and the length of the supply chain has often contributed to better performance in responsiveness, lower cost, better quality of the product, and better resilience of the supply chain despite disruptions (Mena, et al., 2013; Ang, et al., 2016). Typically, companies with a diverse portfolio of suppliers have more flexibility when it comes to disruptions within the supply chain. The automotive industry, specifically Toyota Motor Corporation, did not have a diverse portfolio, therefore when tsunamis hit the geographical location where its suppliers' manufacturing facilities were located; there were no alternative suppliers to assist with the shortages of the parts needed. Toyota only had first tier and second tier suppliers (Yoon, et al., 2019). The tsunami that disrupted Toyota happened in 2011, and in 2019, Toyota was affected again by Covid-19 (Belhadi, et al., 2021). Toyota and other companies realize that having multiple suppliers in different locations in a supply chain matters when it comes to risk, resiliency, and flexibility. The tsunami made many companies aware that disruptions can go far beyond the first-tier supplier, and when the Covid -19 pandemic occurred, companies realized that the performance of a supply chain can be affected by how complex and how many tiers and locations the supply chain consists of (Ang, et al., 2017).

With the sudden urgency for companies to improve their supply chain performance, the management of supply chains has become an acute focus with most companies. Supply chain management has several definitions in the literature. The Global Supply Chain Forum (GSCF), a group of non-competing firms and a team of academic research defines supply chain management as "the integration of key business processes from end user through original suppliers that provides products, services, and information that add value for customers and other stakeholders" (Lambert and Cooper, 2000). Another view is that supply chain management is a coordinated, planned function of the business that integrates the supply chain players to improve the overall business functions long-term performance (Mentzer, et al., 2011). APICS, the association for supply chain management, defines supply chain management as "the functions within and outside a company that enable the value chain to make products and provide services to the customer" (Lummus and Vokurka, 1999).

The definitions of supply chain management are somewhat similar throughout the literature; however, the definition of disruptions can vary. A supply chain disruption is an unexpected event that obstructs the normal flow of information and material (Craighead[1] et al. 2007) with potentially negative consequences to supply chain members and customers (Chopra and Sodhi 2004; Blackhurst, Dunn, and Craighead 2011). Disruptions can be described as unforeseen and involuntary events that cause business operations either upstream or downstream to function abnormally (Messina, et al., 2020). Disruptions can be natural or man-made disasters ranging in severity (Messina, et al., 2020).

Disruptions in the supply chain can be detrimental or disruptions can cause a minor problem, as when a machine breaks down at a manufacturer's location. Disruptions in a supply chain can be hard to define as there are many disruptions that occur daily, and some disruptions can occur only once in a lifetime. According to the literature, all experiences can be defined as a disruption if they have an unforeseen nature and cause a business to operate in less-than-ideal conditions (Messina, et al., 2020).

Disruptions can vary in severity and in frequency and resiliency of a supply chain can help mitigate the disruption's effect. Resiliency is defined in similar ways throughout the literature, with a key factor noted in many articles; resiliency is a supply chain's ability to recover from disruptions and is key attribute to the success or the downfall of the entities involved throughout the supply chain (Singh, et al., 2019; Behzadi, et al., 2020). To measure disruptions, this study will use three metrics: geographical scope, the severity of the disruption, and the duration of the disruption. Rahman[2], (2021) suggests that a disruption lasting longer than a month occurs every 3.7 years on average. Understanding how well the supply chain functions during a disruption and how quickly the supply chain can recover will allow us to measure the resiliency of the supply chain. This, in turn, will shed light on what characteristics help a supply chain to be resilient despite the unexpected events that may occur.

Researchers also suggest that resiliency in a supply chain consists of many different characteristics. Some researchers state that the supply chain must have visibility, or the ability to share information across supply chain entities (Messina, et al., 2020). The information can consist of process or transactional data, logistical planning, product activities, or supply procedures (Messina, et al., 2020). Other aspects which may improve resiliency, albeit at an increased cost, include larger amounts of safety stocks at different points in the supply chain. Similarly, having access capacity may enable the supply chain to handle some disruptions. Supplier selection in terms of number of suppliers and their geographical dispersion can increase or decrease resiliency. For example, while Just-in-Time (JIT) inventory management prescribes using fewer suppliers, this can cause problems when the fewer number of suppliers are unable to deliver compared to several suppliers in diverse regions that are able to deliver, as the disruption in the supply chain did not affect them. Having a diverse portfolio of multiple suppliers in different geographical locations can increase the capacity of the business to obtain goods when needed, despite problems within the supply chain.

Is there a way that we can accurately figure out how to mitigate the effects of disruptions in the supply chain for the future? In the past, trying to study disruptions in a supply chain can be challenging using analytical models due to supply chains complexity; however, agent-based modeling (ABM) has enabled researchers to create simulations that can be complex, yet realistic to understand how a supply chain functions when it is disrupted. In this study, we will create an ABM, using NetLogo, and test the supply chain to understand how it will react to disruptions that are either repeatable (frequent) or non-repeatable (very infrequent).

The purpose of this research is to examine the impact of management decisions on the structure and operations of the supply chain on its resilience and its financial performance.

These managerial decisions include:

1. The amount of excess capacity at each entity of the supply chain (Wong et al. 2020).

2. The raw material and finished goods safety stock at the different entities of the supply chain (Adhitya et al. 2009).

3. The number of first and second tier suppliers (Nie et al. 2018).

4. The geographical dispersion of the suppliers (Nie et al. 2018).

The resilience of the supply chain is measured by the following metrics (Behzadi et al. 2020).

1. The service level (% of demand satisfied from existing inventory) during a disruption.

2. The time needed to return to normal operations, in both customer service and profitability.

3. The decrease in profit due to the disruption.

4. The lead time during the disruption.

A single type of supply chain does not capture the diversity of supply chains in real life; therefore, we will examine three types of supply chains, customer-focused, low-cost, and dual-purpose. Customer-focused supply chains carry large amounts of safety stock and have short lead times. Low-cost supply chains have a very low amount of safety stock and have long lead times. Lastly, the dual-purpose supply chain has a moderate amount of safety stock and moderate lead times.

Our analysis will examine the effects of repeatable as well as non-repeatable events. For the purposes of this study, non-repeatable events will be defined as events that are very infrequent, but their effects are global, resulting in major disruptions throughout the supply chain. Repeatable events will be defined as events that happen often, can be caused by natural disasters, such as hurricanes and tornadoes, or man-made such as strikes, but can cause either minor or major disruptions throughout the supply chain.

To answer the above questions, we develop an ABM simulation of a supply chain. ABMS have become popular in the last 20 years, as other modeling options were unable to deal with complex dynamic problems with many players (Tisue, et al.,2004). Netlogo, the software program that will be used to code our ABM, can “model complex systems evolving over time” as well as perform complex mathematical computations (Tisue, et al., 2004). Many researchers use ABM simulations and there are many advantages. The modeling will allow researchers to quantify information, has modularity, has great flexibility, large expressiveness, and the possibility to execute the simulation in parallel (Helbing, 2012). Another advantage is that ABM can simulate intricate systems with independent, yet intertwined entities (Wu, et al., 2013). The ability to simulate systems with independent entities is a key factor in understanding how each entity is affected adversely or positively when supply chain disruptions cause significant chaos throughout the chain. Of course, each entity can feel the effects of a disruption differently and ABM will allow measurements at each echelon of the supply chain. Lastly, a large benefit to ABM is that researchers can simulate complex real-world problems, and understand the outcomes, without spending the money and time it would take to study the actual scenario in a business.

The rest of this dissertation is organized as follows. In section 1.2, we review related literature. In section 2, we describe the supply chain configurations and decisions used for the purpose of this dissertation. In chapter 3, we describe an ABM of the supply chain. We analyze the results from the simulation in Chapter 4 and close with a conclusion in Chapter 5.

1.2 LITERATURE REVIEW

It is important to note that Covid-19 is not our only major supply chain disruption. There have been epidemics, financial crashes, tariffs, strikes, hurricanes, tsunamis, floods, and tornados. Disruptions have different effects on the supply chain according to the severity of the disruption, but Covid-19 has affected supply chains the most as it was a global pandemic. According to Craighead[2], Ketchen, Jr. and Darby (2020), there are 3 dimensions that make Covid-19 different from other supply chain disruptions that we have had in the past. The dimensions include the scope. The scope refers to the geographical location of the disruption. The scope can be small, e.g., a union/labor strike on the California coast. The scope can be large, e.g., Covid-19. The second dimension is the spillover that occurs when there is a disruption. We can also call this spillover the "ripple effect" (Ivanov et al., 2020). Spillovers are defined as smaller disruptions that cause a ripple effect, causing the disruption to be large, creating "ripples" throughout the supply chain. Often it is hard to recover from large spillovers. Finally, the last dimension is called a shift. A shift occurs when a company goes out of business. Consumers may go elsewhere to get a product. However, during a pandemic there is a huge shift in demand as the products that people normally buy are no longer available. The article uses a great example for the shift of the supply chain. While everyone was buying soft, residential toilet paper because people were staying at home more, the demand for industrial toilet paper with large rolls decreased causing the shift in demand (Craighead[2] el at., 2020; Grossman and Helpman, 2020).

As we mentioned earlier, our metrics for measuring a disruption are the scope, severity, and complexity.

Two streams of research in operations management are relevant to this work, supply chain disruptions and supply chains resilience and risk management. Researchers have used different methodologies including analytical, empirical, simulation, and qualitative (Pournader, et al., 2020[1]). The research includes ABM simulation methodology in supply chain disruptions and supply chains resilience and risk management. Because of the vast volume of previous studies, we will focus our review on literature from 2000 to the present time. We focus on the relevant literature which used agent-based modelling simulation and analytical methodologies as they are closest to our work.

1.3 AGENT-BASED MODELING SIMULATION (ABMS)

Often, researchers use simulation to answer the “what if” questions in supply chain. ABM simulation is a useful tool and can give us insight into how the supply chain will react to certain disruptions. ABM is a newer concept that is different from the older simulation techniques in that the agents in the simulation are independent and follow a set of rules that are predefined by the researcher; however, the agents can also interact with the environment and other agents that are within the simulation (Maidstone, 2012; Macal and North, 2009). Before ABM, simulation methods included discrete event simulation (DES) and system dynamics (SD) (Maidstone, 2012). DES looks at a computation of discrete events, as the name suggests, while SD looks at the flows between entities. As supply chains are constantly growing and changing, the need for a realistic way to model them is highly desirable to both researchers and practitioners. The thoughts are that if a supply chain can be modeled accurately, then the outcomes can be measured and used to handle supply chain disruptions enabling the supply chain to become more resilient. The need for ABM simulations (ABMS) is growing considerably for this reason. Complexity has always been difficult to model and until recently, the complexity was difficult to realistically model (Macal and North, 2009).

Agents in ABM can range in definition between different researchers, and to understand how ABM works, we need to understand its unique feature in that agents can interact with other agents. The agent behavior is important when building a simulation in that one agent can affect how another agent reacts to disruptions or other activities that a researcher wants to simulate. Economic modeling prior to ABM relied on a "perfect market" and now, that modeling can incorporate a more accurate and realistic behavior (Macal and North, 2009). Next, the agent must be independent. Independency for the purposes of this study describes that the agent can function by itself in an environment with other agents. An agent must also have its own set of attributes that will help determine if that agent will or will not respond to certain events that are modeled within the simulation. Agents can respond to their environment and other agents that are also in that environment. Agents typically have a set of rules and have resource properties and have a decision-making ability to guide their behavior in the simulation (Macal and North, 2009).

Rahman[2], et al (2021), created an ABMS to understand the recovery from the disruptions of the pandemic in reference to the demand for facemasks. They sought to understand the following areas in supply chain: the effects of a major disruption (a non-repeatable event) on the manufacturing of essential items, recovery plans to keep the supply of essential items, and what types of changes can be made in the manufacturing process to implement the recovery plans. In the simulation, a baseline total supply chain cost was computed. With the disruption of the pandemic, several recovery scenarios were simulated to minimize the total supply chain costs given the major disruption. The first scenario of recovery included a large stock of raw materials to ensure that the demand could be met. The second scenario included increasing the production capacity. Within the increased capacity, different recovery plans were simulated. Each scenario included increased capacity for either a long term or short-term recovery including a 50% increase of utilized capacity or a 100% with a long term or short-term recovery plan. The outcome of this study suggested that a recovery plan with a high utilization capacity 100% over a short period of time would yield the lowest short-term total supply chain costs.

In Li and Chan (2012), stocking strategies are modeled as agents. ABM was used because most simulations did not allow non-linear relationships; however, ABM could be used for that purpose. In this study, the simulation modeled make to order and make to stock inventory. As mentioned above, the study allowed for certain agents to have certain criteria or attributes. The conclusion noted that more complex applications could be modeled and studied easily using ABM (Li and Chan, 2012).

Wu et al (2013), developed a model to simulate retail stockouts to understand how the disruption for certain products affected the supply chain. The simulation could also assist in understanding the effect of consumer behavior as consumers will behave in one of different ways when stockouts occur. First, the consumer can opt not to buy anything, and that demand is lost, the consumer can opt to buy a substitute product, or the consumers would wait until the product was back in stock. The first two behaviors ultimately lead to a decrease in market share over time.

Riddle, et al (2021) used ABM to analyze disruptions in the rare earth elements (RRE) supply chain. Problems in China, the main supplier for RREs, can cause severe disruptions as the geographical location for RREs can be specific, often taking years to procure the RREs from another region. The researchers wanted to build a simulation that could help them answer the following questions: Do the consequences of disruptions differ by the type of disruption and why does it differ? How does China's dominance in the RREs affect the previous consequences mentioned? And lastly, how will RRE trade be affected by supply chain disruptions? To answer these questions, disruptions scenarios were simulated. The disruptions included a temporary production loss, permanent capacity shutdown, and a supply diversion. Ultimately, the conclusion was made that the price of certain materials (RREs) could increase substantially depending on the type of disruption. If the disruption causes the supply chain to seek materials outside of China, the other geographical locations may not be able to handle the demand, causing the cost of RREs to increase exponentially; therefore, driving the demand down.

Colon et al. (2021) developed an ABM to improve our ability to understand and assess the consequences of natural disasters. The model describes the interactions in space and time of a transport–supply chain and allows the tracking of how a disruption at network nodes or links perturbs the flows of goods in supply chains and how these perturbations both households and firms. Along the same lines, Naqvi and Monasterolo (2021) used ABM to analyze the indirect impacts and cascading effects of natural disasters and the post-shock transition phase. This model embeds heterogeneous spatial and temporal preferences, asymmetric information, and path-dependent post-shock outcomes.

Dulam et al. (2020) focused on the effect of panic buying by consumers when a natural disaster occurs. In this AMB, a disaster causes panic buying among consumers, resulting on a supply chain disruption. The effectiveness of some strategies, e.g., limiting sales per person, to control demand are analyzed to understand the effect on the supply chain. Continuing to focus on panic buying, Rahman[3] et al. (2022) analyzed essential-products supply chain instabilities they cause via an ABM in the context of Covi-19. Supply chain performance was measured using few measures including total supply chain costs, manufacturing costs, inventory costs, and shortage costs. In a related work, Upton and Nuttall (2014) developed an ABM simulation to analyze the transient need of the supply chain and consumers during fuel crisis event and used the fuel panic crisis in the UK in 2000 and 2012 to verify their results.

Lohmer et al. (2020) examined resilience from a technological experience by understanding how blockchain technology can enable the supply chain to exchange data that is transparent, rapid, and protected, thus allowing the supply chain to recover quickly from disruptions. Three types of supply chains were measured, high efficiency, medium efficiency, and low efficiency. To measure the effect on the supply chains, ABM was used to simulate a simple supply chain for baseline product flow without blockchain technology in the wake of a disruption. Holding costs, demand, profit, recovery time and capacity of each entity were used to quantify costs during disruptions. After the baseline was established, the model was then simulated again, but with the aid of blockchain technology. The ABM simulation showed that there was a significant decrease in overall disruption costs compared to the baseline model. The longer the disruption, the more the block chain technology aided in resiliency within a high efficiency supply chain. During short-term disruptions without the use of blockchain technology, the low efficiency supply chain suffered exponentially.

Carvalho et al. (2012) assessed resiliency during disruptions for an automotive supply chain usingABM. In this simulation, a three-tiered supply chain was modeled with 1st. 2nd, and 3rd tiered suppliers. Two supply chain strategies were tested: redundancy, and flexibility, where redundancy is reliant on safety stock and flexibility is reliant on reconfigured transportation networks. Two main values were measured to evaluate resiliency for each strategy: the lead time ratio, and the total cost. The lead time ratio is the difference between the actual delivery time versus the agreed delivery time. The total costs are the sum of the production cost, material cost, inventory holding cost, and the transportation cost. The ABM model simulated 6 different scenarios and while both strategies helped mitigate the disturbance, the redundancy strategy improved the lead time ratio, and the flexible strategy enabled the total cost of the supply chain to decrease.

Dorigatti et al. (2016) explored supply chains without a dominant member who provided the main knowledge. With the main entity taking a more collaborative approach to the supply chain in prioritized a service-oriented framework. In order to test this theory, ABM was used to simulate a supply chain that had collaborative players for a company in Argentina that produced dairy products. To understand the difference between having a main entity driving the supply chain, and having a more collaborative supply chain, there were two different coordination strategies implemented. The first strategy used the distribution center as an independent player, or as the driving force behind the supply chain. Each distribution center completed its own forecast independently of the other players in the chain. The second strategy consisted of a single entity making the inventory decisions while looking at the entire supply chain, and not just one single distribution center. Revisions of the orders were also studied within a short window, weekly and a long-term window, 180 days. The conclusion of this study indicated that the benefits of a collaborative supply chain is difficult to estimate in a real-world situation; however, ABM is an effective, inexpensive tool that can be used to simulate the effects of management decisions within a supply chain. Overall, the simulation showed that having a centralized supply chain created better service levels in fulfilling orders and revisions in the short-term period were comparable to the long-term window.

Achmad et al. (2021) concentrated on robust optimization (RO) to optimize the rice supply chain given uncertainty in labor and capacity due to the pandemic. The uncertainty with labor arose when workers would be infected with the Covid-19 virus, causing them to be out of work. Using ABM, the spread of the virus was simulated. Relationships between agents were analyzed as well as relationships between agents and the environment, affected and not affected with the virus. Geographical location also played a part in this simulation, as the spread of the virus would be higher in some locations. ABM was a key component of this study as real data was unavailable and although a true analysis of this study is difficult, the simulation can mimic the relationships. NetLogo was used to create the simulation. RO method helped deal the uncertainty and resulted in the uncertainty being solved by the robust counterpart methodology.

Lau et al. (2006) relied on ABM to understand distributed scheduling, which allows single entities to make decisions based on the location, infrastructure, and constraints of the entity. Then those decisions are integrated into one centralized data location so that other entities can view and respond to the information accordingly. Often a source of information that is accurate and shared across the sectors of the supply chain is hard to obtain, but with ABM, distributed scheduling can be simulated to create usable data. In this study, several approaches are simulated to understand how distributed scheduling can be obtained within entities that are independent from each other. A centralized heuristic approach was simulated where all information was shared across each entity as well as a contract-net protocol method that involved minimal information sharing. Lastly, a modified version of a contract-net protocol simulation that involved a combination of the generic contract-net protocol and the central heuristic approach where information was shared was simulated and analyzed. The conclusion of this study resulted in the modified contract-net protocol outperforming the generic contract-net protocol and the modified version of the contract-net protocol performed comparatively with the centralized heuristic method.

Rahman[1] et al. (2022) used ABM to simulate a potato supply chain and the disruptions due to climate changes affecting various levels of the supply chain. The study involved 5 key players in the potato industry, farmers, shippers (act as buyers of raw materials, then they sell the product to larger industries), processors, retailers, and logistic companies. To compute the optimal base price for potatoes, a model was developed using data from 2006-2019. Once the price for the potatoes was calculated, the price was adjusted according to demand and the supply that farmers could produce monthly. Revenue, lead time, potato price, and the amount of potato inventory that was either bought or sold were used for the overall performance metrics analyzing the data output from the simulation. Disruptions included a drought and extreme weather (defined as an early frost). A model without disruptions was run first to obtain the baseline metrics. Once the baseline was established, the impact of the disruptions was measured resulting in an increase in potato prices of 69% due to a drought. An extreme weather event caused farmers to lose 30% of their yield, resulting in an increase in price of 20.2%. The major increase in potato prices caused customers to buy processed potatoes, resulting in a 2.8% revenue loss of processed potato sales, as the purchase price for the retailers from the processors is higher.

ABM has also been used to analyze the spread of viruses such as Covid-19. Shamil et al. (2021) developed an ABM to model the spread of COVID-19 among the population of a city. The ABM can be adjusted to accommodate any location by using parameters specific to the city. Infected individuals can transmit the disease in their various daily activities. Ying and O'Clery (2021) developed an ABM for virus spread in a supermarket. Shopper (agents) move about the supermarket for some amount of time and come to close proximity other infectious customers. The model was tested on a synthetic store and shopping data to show how it can be used to estimate the number of infections due to human-to-human contact in stores. Similarly, Cuevas (2020) developed an agent-based model to evaluate the transmission risks of COVID-19 in facilities. The ABM incorporated the spatiotemporal transmission process and agents made their decisions depending on the programmed rules. Such rules correspond to spatial patterns and infection conditions under which agents interact to characterize the transmission process. An individual profile for each agent, which defines its main social characteristics and health conditions are also considered.

ABM has also been used to simulate vaccine distribution. Li and Huang (2022) developed an ABM to simulate virus transition among a sample of 198 million people in 148 countries using advanced computational services. A comparison of strategies of achieving minimum vaccination rates and allocating vaccines based on pandemic levels was performed using the simulation. Zhou et al. (2021) used ABM to optimize vaccine distribution strategies which incorporated spatial priorities. Four vaccination strategies (random strategy, age strategy, space strategy, and space and age strategy) were tested and the optimal strategy was identified. Asgary et al. (2020) combined discrete event simulation and agent-based modeling techniques to develop a drive-through vaccination simulation. The simulation shows the average processing and waiting times and the number of cars and people that can be served under different number of servers, channels, screening, registration, immunization, and monitoring times.

Another use of ABM is in the analysis of evacuation plans in case of a disaster. Na and Banerjee (2019) developed an agent-based discrete-event simulation with an embedded geographical information system module for making no-notice natural disaster evacuation plans. Furthermore, to examine the applicability and extensibility of the proposed integrated GIS-based ABDES modeling framework, experiments were used to test the system using several realistic scenarios of San Francisco in California. Kim et al. (2022) developed an ABM to analyze a short-notice evacuation plan for the city Waikiki, Hawaii. The ABM estimates populations exposed to harm, evacuation times and deaths for a catastrophic tsunami event. Three travel modes: pedestrian bicycle, and motor vehicles were considered in this ABM. In addition, ABM was also used for studying classroom evacuation Delcea et al. (2020). The ABM is easily configurable in various

classroom settings. Five types of classroom configurations were used. In addition, the presence of jumped and bypassed obstacles and guidance from volunteers were considered. A review on the use of ABM for evacuation analysis and planning can be found in Kaur and Kaur (2022).
In sum, the literature for ABM is vast, and this modeling technique can be used for many different supply chains and for many different scenarios with a very realistic approach to problem solving within the context of each unique situation. Several different software was used to create the ABM but for the purposes of this study, I will be using NetLogo 6.3. The software enables us to set up different echelons of suppliers, factories, customers, and distribution centers in different geographical locations. NetLogo was developed at Northwestern University's Center for Connected Learning and Computer-Based modeling and was developed to aid in teaching (Macal and North, 2009). NetLogo is a free platform and can model multiple agents in a complex environment, accurately depicting a supply chain with a time lapse element (Ni, et al., 2018).

1.4 ANALYTICAL MODELS

Analytical methodologies are commonly used to study supply chains. Often the studies are based on a mathematical model describing the relationships in the supply chain. The model is based off stagnant "agents" that mostly do not adapt and change. The area of analytical modeling for managing and mitigating supply chain risk is vast. Many literature reviews have been conducted in this area. For example, a meta-analysis conducted by Snyder, et al. (2015), reviews 180 scholarly works using analytical modeling methodology for supply chain disruptions. Disruptions being defined as unplanned events that cause a halt of a supply chain, either completely or partially for an undetermined amount of time. To compare the articles, the supply chain modelling implies that the supply chain can be one of two states; either up or down, implying that up means the supply is fully functional and down means that the supply is at a standstill. Both up and down interval durations are assumed to be exponentially distributed for any model requiring a continuous time frame as well as requiring parameters that are coined disruption and recovery rates. However, for discrete time models, the duration is geometrically distributed, and disruption and recovery probabilities are coined to explain the parameters as the Markov model is used, assuming that no prior disruptions are affecting the current disruptions.

Snyder, et al. (2015), reviewed literature on inventory's role in disruption mitigation. If the service level is high, then disruptions can be mitigated; however, modelling is used to create an algorithm to understand the service level that should be attained when potential disruptions can occur. This literature review by Snyder, et al. (2015) addresses the previously used multi-echelon modelling where a node has only one predecessor, disruptions can occur in a multi-echelon supply chain that has different configurations. ABM will allow us to use a multi-echelon configuration where nodes can have several predecessors. In another example, an analytical model methodology approach was used to understand the resilience of supply chains and the different layers of echelons within the supply chain. The analytical model used was data envelopment analysis (DEA). The data envelopment analysis allowed researchers to evaluate different entities together with several attributes in the supply chain. They concluded that DEA can be used to synthesize system wide and echelon specific approaches (Pournander[2], et al., 2016).

Several other analytical modelling approaches are discussed by Snyder, et al. (2015) but one other option that we will discuss concerns mitigating disruptions by geographical location. ABM will also incorporate geographical location and according to this meta-analysis, the main concern centers on the physical location of the facilities and the cost of these facilities. If the locations are geographically different, should that add to the cost of the facilities? The answer to this question is yes, and that should be considered when understanding that the geographical location will have a different impact according to the scenarios presented with each disruption.

In another comprehensive literature review, conducted by Bier, Lange, and Glock (2019), 77 articles were reviewed. The articles included analytical methods, giving an overview of findings from several areas of focus that closely aligns with the focus of our research. The authors divided the supply chain analytical modeling articles to include those focused on certain methodologies to analyze risk effects on the supply chain during disruptions. Also included in the review, were the methods that seek to understand the risks during disruptions and how those risks indirectly effect the supply chain. The review sought to answer three questions involving risk and disruptions using analytical models. One question sought to explore how research in this particular area had evolved over time, and the conclusion was that the area of risk and disruptions had received increased attention in academic literature. The complexity of supply chain modelling was addressed in the second research question. Research in the literature showed that multiple networks were used to model complexity, and the nodes within the network could have numerous implications. Lastly, the review classified the methods and ultimately, the analytical quantitative method was among the most utilized for understanding risk and disruptions within the supply chain.

Shen and Li, (2016) published a literature review including 30 articles focused on supply chain disruptions. Disruptions included natural disasters, as well as unintended disruptions caused by individuals. To focus on the disruptions even further, Shen and Li, (2016) proposed that demand and supply are the two major facets of disruption. In the meta-analysis, the SARS (severe acute respiratory syndrome) hit China, certain supply and demand functions changed as the disruption caused a shift it both. Covid-19 also caused the same type of supply and demand shift as people started to stock up on certain items, and other items were no longer a priority. With either a natural disaster or a pandemic, demand modelling was utilized to understand the shift that had occurred. The demand modelling also indicated if the price should rise or fall because of demand.

Models in which stockpiles of essential products are held to mitigate the effects of a disaster have also been developed. Hammami et al. (2023) considered the decisions of a government on the inventory stockpile to hold of personnel protective equipment (PPE). The government can also provide a subsidy to manufacturers to move production on-shore. The model determines the optimal mix of PPE stockpile and subsidized local production to meet the demand spike that can be brought about by a disaster. Khouja and Hammami (2023) applied game theory for pandemic preparedness in terms of satisfying the needs for PPE products by a budget-constrained governmental organization (GO). In this model, the manufacturer maximizes profit, and the GO maximizes preparedness, measured by the service rate of PPE. The manufacturer supplies the PPE stockpile in the first year and buys back older PPE from the GO and sells it new PPE each year after that. The manufacturer sells older PPE in the marketplace.

Ding et al. (2022) analyzed the effects of various supply chain node disruptions on the performance of a dual channel supply chain. The supply chain can be disruption-free, or a disruption can occur at the manufacturer, the warehouse, or the offline store. The simulation was coded in AnyLogistix. The findings indicated that supply chain node disruptions decrease the service level of the supply chain. Furthermore, disruptions at the warehouse have the most negative effect on the performance of the supply chain. In our model we extend the supply chain to include tier one suppliers with different cost, geographical, and lead time characteristics.

Some models in the literature used financial methods to deal with supply chain disruptions. For example, He et al. (2019) used real options pricing methodology to determine the optimal expected profit-maximizing order quantity that allows for disruption risk mitigation in a two-stage supply chain. Zhang et al. (2021) considered holding capital reserves for pandemic preparedness. Capital reserves may be held in addition to inventories of medical supplies. They showed that for products with perishable nature demand uncertainty results in less safety stock and larger capital reserves. Ghadge et al. (2021) focused on financial risk in a two-echelon supply chain and formulated a multi-objective decision model for supplier selection which also determines order allocation. The model maximizes the profit of the manufacturer and minimizes financial risk faced by selected suppliers. Zhang et al. (2021) used the Value at Risk (VaR) framework to develop a recovery time equivalent (RTE) disruption risk measurement model. The model provides managers with a tool to examine 'what-if' questions about vulnerabilities of their supply chain. Fan et al. (2023) examined the use of catastrophe financial insurance for supply chains operating in a disaster-prone environment. The authors developed a stochastic programming model of a global multi-echelon supply chain to analyze the impact of purchasing catastrophe insurance on supply chain operational planning.

In a more recent work, Cao et al. (2022) developed a model of a supply chain which is subject to uncertain disruptions causing a decrease in production capacity at its facilities, resulting in cascading failures along the supply chain network. The model studies a robust network design and recovery investment fund which are used to help the supply chain. Liu et al. (2023) analyzed the impact of government intervention to mitigate the ripple effect of a disruption in the supply chain. The authors developed two mathematical programming models to minimize disruption risk for a government with a limited budget. Sawik (2023) developed a stochastic quadratic optimization model for a supply chain experiencing disruption. The goal of the model is to maintain supply chain viability as the effect of the disruption ripples through the chain.

CHAPTER 2: GENERIC SUPPLY CHAIN

In this chapter, we provide a description of the generic structure of the supply chain and the management of a generic supply chain. The structure of the supply chain is represented by the number of tiers, the number of entities at each tier, and the connectivity between the entities and the different tiers. The management of the supply chain is represented by long-term and short-term decisions. Long-term decisions refer to capacity and location decisions. Short-term decisions are day-to-day decisions including lot sizing and safety stock for raw materials and finished goods. Pricing is considered a long-term decision related to the positions of the supply chain in the industry. We begin by describing a generic supply chain structure and follow it with supply chain management. Then we will follow the generic supply chain information with the supply chain model used for our Netlogo simulation.

2.1 GENERIC SUPPLY CHAIN STRUCTURE

Supply chain structure can be as simple as one small family-owned country store supplied by few manufacturers, or larger supply chains can consist of many different organizations from across the world. Since our goal is to examine the resiliency of supply chains when subjected to a disruption, our supply chain needs to be representative of a real-world supply chain. As such, the supply chain should allow for geographical considerations which incorporate countries as well as regions within a country. The supply chain should also operate with realistic management decisions. In this generic supply chain model, many questions about the supply chain can be examined and answered. In the Netlogo model, we will focus on an initial supply chain to examine.

Our general supply chain structure is depicted in Figure 1. We consider a supply chain model with one retailer, denoted by *R*, serving a market which is divided into four different geographical zones, $i = 1, 2, 3, 4$, corresponding to northeastern, southeastern, northwestern, and southwestern United States (US), respectively. The retailer is served by a distributor, denoted by *D,* with four distribution centers, $i = 1, 2, 3, 4$ in each zone and stores in zone R_j are supplied by distribution center D_j but can also be supplied from other distribution centers D_i, $i \neq j$ at an increased cost.

The distribution centers are supplied by a manufacturer, denoted by *M,* with four production facilities, $i = 1, 2, 3, 4$ in each zone. Distribution center D_j is supplied by manufacturing facility M_j but can also be supplied from M_i $i \neq j$ at an increased cost.

The suppliers are denoted by $T_{i,j}$, where i denotes the tier of the supplier and j denotes the supplier number within its tier. There are two tiers of suppliers. In tier 1, there are four suppliers $T_{1,t}$, t = 1, 2, 3, 4 where $T_{1,1}$ and $T_{1,2}$ are domestic. $T_{1,3}$ and $T_{1,4}$ are global suppliers. There are also four tier two suppliers $T_{2,t}$, $t = 1, 2, 3, 4$, where $T_{2,2}$ and $T_{2,2}$ are domestic. $T_{2,3}$ and $T_{2,4}$ are global suppliers.

We assume that all Tier 2 suppliers and Tier 1 suppliers have full connectivity. In addition, Tier 1 suppliers have full connectivity to all manufacturing facilities and each manufacturing facility has full connectivity to each distribution center. Likewise, each distribution center has full connectivity to all retail locations.

Our use of an ABM is flexible in terms of modifying the structure of the supply chain in Figure 1. Both the depth of the supply chain, i.e., the number of tiers, and the width of the supply chain, i.e., the number of entities of a given tier can be easily changed. Furthermore, connectivity, which can be used to represent a disruption can be easily changed.

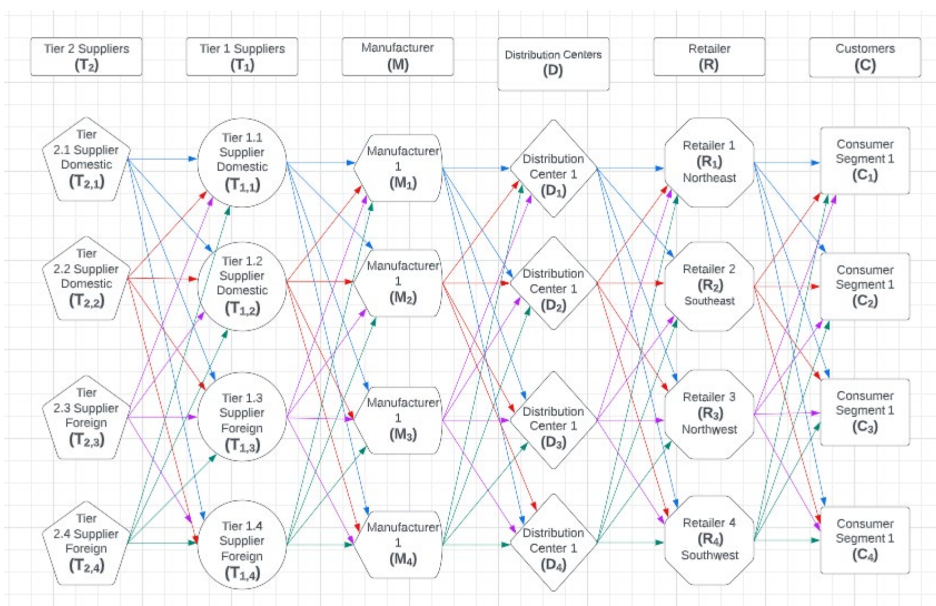

FIGURE 1: GENERIC SUPPLY CHAIN STRUCTURE

2.2 MANAGEMENT OF A GENERIC SUPPLY CHAIN

CUSTOMER DEMAND

For simplicity, we assume all 4 regions are identical in market size denoted by *N* consumers. We assume consumers have uniform reservation prices *R* on, i.e., $R \in [0,1]$. Since all four regions are similar, we use *P* to denote the price (i.e., we drop the subscript *i* as they are all identical). This results in a demand in region *i.*

$$D = N\int_{P}^{1} f(R)dR = N(1-P)$$

The retailer buys from the closest distribution center (i.e., the distribution center with the lowest shipping cost) but can buy from other distribution centers and pay a higher shipping cost. The retailer buys for a wholesale price, w_1; therefore, the retailer's profit is the product of the demand and the margin per unit, $(P-W_1)$

$$Z_r = D(P-W_1) = N(1-P)(P-W_1)$$

Since $\frac{d^2Z_r}{dP^2} = -2N < 0$, Z_r is concave and the sufficient condition for optimality is obtained by solving the first order condition $\frac{dZ_r}{dP} = 0$, which yields

$$p^* = \frac{1 + W_1}{2}$$

THE DISTRIBUTOR

The distributor's profit is the product of the demand and the distributor's margin $(W_1 - W_2)$, where W_2 is the wholesale price of the manufacturer.

$$Z_d = N(1 - P)(W_1 - W_2)$$

Since $\frac{d^2Z_d}{d\mathrm{W}_1} = -N < 0$, Z_d is concave and the sufficient condition for optimality is obtained by solving the first order condition $\frac{dZ_d}{dW_1} = 0$, which yields the following:

$$W_1^* = \frac{1 + W_2}{2}$$

MANUFACTURER

The optimal price of the manufacturer is the product of the demand and the manufacturer's margin $(W_2 - c)$, where W_2 is the wholesale price of the manufacturer.

$$\mathrm{Z}_m = \mathrm{N}(1 - P)(\mathrm{W}_2 - c)$$

Since $\frac{dZ_m}{dW_1} = -N < 0$, Z_m is concave and the sufficient condition for optimality is obtained by solving the first order condition $\frac{dZ_m}{dW_1} = 0$, which yields:

$$W_2^* = \frac{1 + c}{2}$$

Substituting for W_2^* into W_1^* we obtain

$$W_1^* = \frac{3 + c}{4}$$

Substituting for W_1^* into p^*

$$p^* = \frac{7+c}{8}$$

Using W_2^* into W_1^* and p^*, and Z_d, Z_r, Z_m, respectively, we obtain the optimal profits:

$$Z_d = 4\,[\tfrac{1}{32}(1-c)^2\text{N}],$$

$$Z_r = 4\,[\tfrac{1}{64}(1-c)^2\text{N}],$$

And

$$+Z_m = 4\,[\tfrac{1}{16}(1-c)^2\text{N}]$$

Similar, we obtain the optimal demand per region as

$$D^* = N\left(1 - \frac{7+c}{8}\right) = \frac{N(1-c)}{8}$$

TABLE 1: SUMMARY OF NOTATION

Entities and subscripts	**Definition**
$k = D, M, R, T_t$	Distributor, manufacturer, retailer, customer, and tier t supplier
$i = 1, 2, 3, 4$	A subscript denoting USA area, 1: Northeast 2: Southeast 3: Northwest 4: Southwest
$t = 1, 2$	A subscript denoting the tier of a supplier
$j = d, f$	A subscript denoting domestic and foreign, respectively
Parameters	
N	The market size (number of consumers) per geographical area
P	The price per unit of the retailer
W_1	The wholesale price of the distributor
W_2	The wholesale price of the manufacturer
S_M	Setup cost of the manufacturer (can be just S) holding constant global
T	The production rate per year for a manufacturing facility (annual capacity)
I	The inventory holding cost fraction per unit per year
O_k	Ordering cost of for entity $k = R, D$

We assume that the least expensive shipping cost for an entity i is to be supplied by entity $j = i$ at the upstream tier, e.g., it is least shipping cost for the northeast distribution center to be supplied by the northeast manufacturing facility. Therefore, entity i is supplied by entity $j \neq i$ at the upstream tier only if there is a shortage at its least expensive supplier $j = i$, and this results then in an increase in cost of ρ the ordering cost to $(1 + \rho)\ O_k, k = R, D$.

Using the optimal demand, the optimal production quantity of the manufacturer in each facility is

$$Q_M^* = \sqrt{\frac{2D^*S_M}{Ic}}\sqrt{\frac{T}{T-D^*}}$$

The optimal order quantity of each distribution center is

$$Q_D^* = \sqrt{\frac{2\,D^*O_D}{I\,W_2}}$$

The optimal order quantity of each retailer region

$$Q_R^* = \sqrt{\frac{2\,D^*O_R}{I\,W_1}}$$

The total setup and holding cost of the manufacturer (in all four locations) is

$$TC_M = 4[\frac{D^*}{Q_M^*}S_M + \frac{Q_M^*}{2}Ic(1-\frac{T}{D^*}) + SS_M\,Ic]$$

The total ordering and holding cost of the distributor (in all four locations) is

$$TC_D = 4[\frac{D^*}{Q_D^*} O_D + (\frac{Q_D^*}{2} + SS_D) IW_1]$$

The total ordering and holding cost of the retailer (in all four locations) is

$$TC_R = 4[\frac{D^*}{Q_R^*} O_R + (\frac{Q_R^*}{2} + SS_R) IW_2]$$

CHAPTER 3: NETLOGO MODEL IMPLEMENTATION

We have described the full research agenda and now we will describe the implementation in this dissertation. We begin with the supply chain subset structure used in our Netlogo model. The initial model serves as an example to demonstrate what would happen to the supply chain as managerial decisions are made and how those decisions can affect the supply chain when disruptions occur. With the more general model, managerial decisions were examined to understand the impact on the structure and operations on the supply chain with many entities at each tier, and multiple tiers with different geographical locations. To simulate the complexity of the general supply chain model would take several thousands of lines of code, and years to complete. The complete model as described in Chapter 2 is vast, complicated, and would require more time and effort than a dissertation allows for; however, we can take an initial model and examine the listed managerial decisions that are identified in the general model and the measurements required to gain an understanding of a supply chain, its resilience, and how disruptions can affect the supply chain. The Netlogo code used to build this supply chain model can be found in APPENDIX A: Netlogo Code for Supply Chain Simulation.

In Figure 2, the user interface is shown. There are various features and controls that can be manipulated without changing the hard code within the model. These sliders, buttons, and toggles include the following attributes:

- The “setup” button allows the user to delete all prior data and model runs from the simulation.

- Below the “setup" button, there are two buttons with arrows that allow the user to take the simulation one step at a time or to complete an entire run according to our specifications.

- The cycle time is the length of time between ordering products. The cycle time slider can be set from 1 day to 50 days.

- The toggle for the timed run allows the model to stop at a certain number of “ticks” or “days” so that we can calculate accurate profits and lead times.

- The model duration slider is another way the simulation can be stopped on a certain number of “ticks” or “days.”

- The “scenario” slider allows the user to choose which scenario or disruption to introduce to the supply chain. There are 4 scenarios. Scenario 0 is no disruption. Scenario 1 is stopping Supplier 0 (the global supplier) from producing. Scenario 2 halts production from Supplier 1 and 2, both domestic, and lastly, Scenario 3 halts production from all 3 suppliers.

- The “breaks” slider allows the user to choose the duration of the disruption. There are 4 choices, 0 with no disruption duration, 42 with a disruption of 6 weeks, 70 with a disruption of 10 weeks, and 98 with a disruption of 14 weeks. Each “disruption” runs without any disruptions for a total of 10 weeks, and then the “break” is implemented causing the disruption scenario to last for the duration chosen by the user.

- The toggle buttons on the bottom of the interface is another way that the user can disrupt any of the 3 suppliers.

- The toggles for the “supplier price” and the “supplier delay” allow the user to choose any price for any supplier from $1 to $40. The supplier delay toggle allows the user to choose the delay time or the lead time between 1 and 100 days.

- The “SS_Days” toggle represents the safety stock in days and the user can choose a value from 0 to 60 days.

- The demand per day allows the user to choose what daily demand exists from the customer to the retailer. The toggle range is from 0 to 100 units.

- The over capacity toggle range is from 1.0 which represents 100% capacity to 2.0, representing 200% capacity.

- The profit margin range is 0 to 100% and can be changed to the user's requirements.

- The plot length can be changed to allow a broader view of the output on the charts.

- The charts show how the profit will shift from higher or lower depending on the scenario chosen and/or the duration of the disruption that was chosen by the user.

Also in Figure 2, the user interface is shown with all toggles, buttons, and sliders. Each parameter on the interface will allow the user to make managerial decisions and export the data to analyze the best decision to allow the supply chain to suffer only minor consequences when a major disruption occurs or no consequences when a minor disruption occurs.

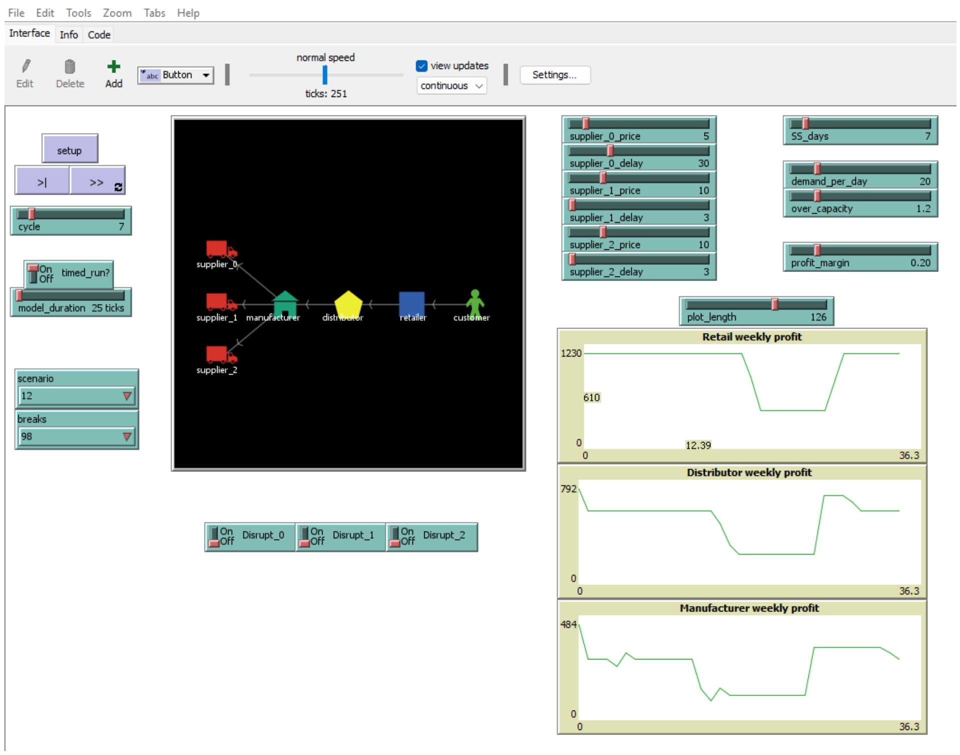

FIGURE 2: NETLOGO INTERFACE FOR INITIAL SUPPLY CHAIN MODEL SIMULATION

In the initial subset model, we streamlined the network as depicted in Figure 3. We assume that the supply chain is synchronized in the cycle time, and each entity uses a cost-plus pricing.

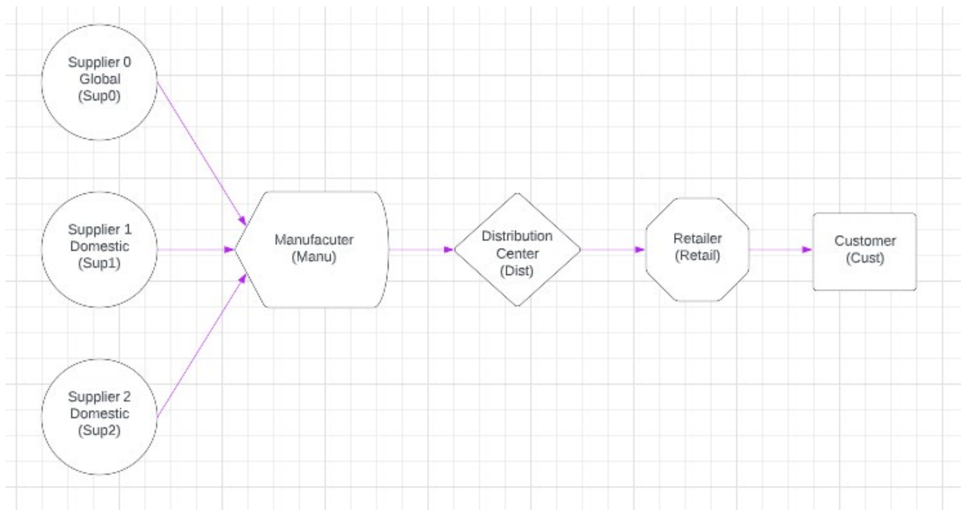

FIGURE 3: INITIAL NETLOGO SUPPLY CHAIN STRUCTURE

In Figure 3, we outline the properties and rules for the initial supply chain model. We consider a supply chain model with an annual demand, denoted by *D,* from a population of *N* customers, denoted by (Cust). Demand_per_cycle, denoted by *DPC*, can be simply calculated as $D\ \times cycle\ time\ (in\ years)$. Once *DPC* is initiated from customers, the demand per cycle prompts the retailer, denoted by Retail, to buy the order quantity, denoted by Q, from the distributor, denoted by Dist. If there is enough product available, the distributor fills the order, which is subtracted from the distributor's inventory, denoted byI_D, and added to retailer's inventory after the lead time. If the distributor does not have enough stock to fill the retailer's order, the distributor must use its safety stock denoted by SS to fulfill the order. All entities have the same amount of safety stock that is chosen by the slider at the beginning of the model run.

The cycle time is set at 7 days, so the distributor buys the order quantity from the manufacturer. The same process is executed throughout the upstream of the supply chain. The manufacturer is supplied by three suppliers, denoted by Sup_0, Sup_1, and Sup_2. Supplier 0 is a global supplier that has a less expensive wholesale price denoted by C_0 and a longer lead time, denoted by $X*L$ ($x>1$), while Supplier 1 and Supplier 2 have a more expensive wholesale cost, denoted by C_1, and a shorter lead time, denoted by L, as both suppliers 1 and 2 are domestic suppliers within closer proximity to the manufacturer. The manufacturer is connected to all three suppliers and depends on each supplier for 1/3 of its supplies so we set the order quantity, denoted by $Q_S = \frac{Q}{3}$, to ensure the quantity is evenly divided between the three suppliers.

We set the price for the global supplier to C_0 = \$10. Both supplier 1 and supplier 2 will have a lower cost per item as they are both domestic and C_1 = \$5. The cost for the manufacturer to buy from the suppliers will be denoted by C_M, as the suppliers have different prices. The cost for the distributor to order from the manufacturer is denoted by W_2 , the cost for the retailer to buy from the distributor is denoted by W_1 Lastly the retailer sells the product to the customer at a sale price, denoted by p. All entities use cost plus pricing. The expressions for prices and profits are shown in Figure 4.

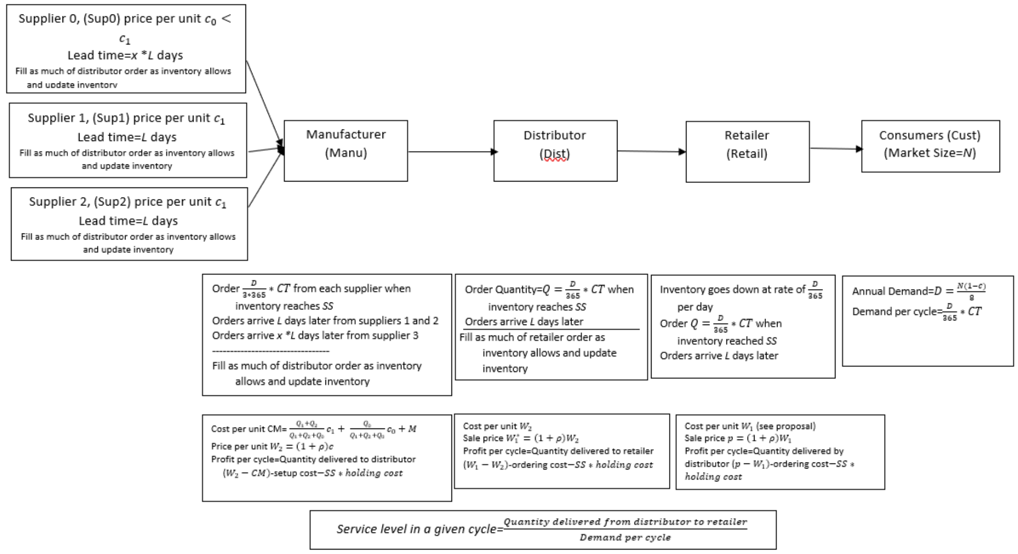

FIGURE 4: INITIAL NETLOGO SUPPLY CHAIN STRUCTURE INCLUDING EQUATIONS

To understand the resiliency of the supply chain, we will examine the managerial decisions listed below. The managerial decisions are identical to the general model described; however, we only have one echelon of suppliers.

1. The capacity at the suppliers

2. The safety stock at each entity

3. The lead time of the global supplier and the domestic suppliers

Resilience will be measured by the following (Behzadi, et al., 2020) in this supply chain subset. These measurements are identical to the measurements identified in the complete model.

1. Service level per cycle, denoted by SL, defined as quantity delivered from distributor to retailer divided by the demand per cycle.

2. Profitability by using cost plus pricing and measuring the decrease in profits.

3. Lead time during the different scenarios and durations of disruptions using service levels and profit loss to understand each scenario.

The disruption will be defined by the severity, which will be depicted by Scenario 1, examining a small disruption with only one supplier shut down. The disruption can be a medium disruption, depicted by Scenario 2 where both domestic suppliers are not producing. Lastly, the disruption can be a large disruption such as Covid-19. We depict a large disruption by Scenario 3, where all 3 suppliers are closed and not making any product. Another attribute of the disruption will be the duration of the disruption. The range can be from 0, no disruption, 42 days, a 6-week disruption, 70 days, a 10-week disruption, or 98 days, a 14-week disruption. Both the severity and the duration can be changed in our simulation to indicate a minor or major disruption.

3.1 TYPES OF SUPPLY CHAINS

For the purposes of this study, we will be studying 3 types of supply chains as shown in Table 2.

1. Customer focused supply chain. This supply chain has a strong focus on customer service. Since this type of supply chain is focused on the customer, often the concerns of the cost of logistics are not at the forefront if the end customer is satisfied. Customer-oriented supply chains carry large amounts of safety stock and have excess capacity for the suppliers and manufacturers.

2. Low cost supply chain. This supply chain configures its structure and manages its operation such that the per unit cost offered to the consumer is low. It holds little safety stock and has little or no idle capacity. The lead times for this type of supply chain are typically longer as it focuses on cost, leading this supply chain to seek out global suppliers.

3. Dual purpose supply chain. This supply chain aims to place itself in the middle range of the low-cost and the customer focused supply chains. As such, it has lead times, excess capacity, safety stock and connectivity that are also around the middle of the two supply chains.

TABLE 2: THREE TYPES OF SUPPLY CHAINS

	Low Cost	Dual Purpose Focus	Customer Service Focus
Safety Stock	7 Day Supply	14 Day Supply	21 Day Supply
Lead Times	30-3-3	30-3-3	30-3-3
Capacity	100% at capacity	20% over capacity	40% over capacity

We will subject the three types of supply chains to disruptions with the following managerial decision parameters while analyzing the profit and the service levels for the retailer.

- Scenario 0, Scenario 1, Scenario 2, Scenario 3, each with various levels of safety stock from 0 days of safety stock to 60 days of safety stock in 3-day increments to understand how the amount of safety stock effects the profitability and service levels to the various supply chains. Regression analyses will be computed to understand the relationship between safety stock held at a location and the profits and service levels associated with each scenario.

- An overview of the retailer’s profitability and service levels with each scenario and the various disruption durations. An overview of the findings will be provided.

- An increase in holding costs from 20% to 40% will be analyzed to understand the increase of profit and service level associated with the increase in costs to each entity during the disruption scenarios coupled with the various durations of those disruptions.

- Scenario 1 for all three supply chain types and various disruption durations will be analyzed with the effect of capacity of 100%, 20% over full capacity, and 40% over full capacity.

- Varying lead times of 15-1-1, 30-3-3, 60-10-10, and 90-20-20 with the first number being the lead time for the global supplier, Supplier 0, and the next two numbers representing the lead times for Supplier 1 and Supplier 2, both domestic suppliers.

- Panic Buying with various scenarios and disruption duration times.

CHAPTER 4: RESULTS

First, we are going to show an overview of the effects of the safety stock amount per day in relation to profits and service levels for each type of supply chain. To examine the results, our simulation model built in NetLogo will need to be run to acquire the data needed to analyze each supply chain with its respective amount of safety stock. A low-cost supply chain consists of lower safety stock to help reduce costs such as holding costs, ordering costs, and setup costs. The low-cost supply chain will have a safety stock of 100% or 7 days. The dual-purpose supply chain will hold a safety stock amount of 14 days or 200%. Lastly, a customer-focused supply chain holds a larger amount of safety stock to ensure there are no stockouts; therefore, it will hold 21 days of safety stock or 300%. After calculating a baseline profit and service level, we will subject each supply chain to different disruptions scenarios with varying durations of disruptions. Scenario 1 will include Supplier 0 (global) halting any production or shipments. In Scenario 2, Supplier 1 and Supplier 2 (both domestic) will halt any production or shipments. Lastly, Scenario 3 will halt all suppliers, Supplier 0, Supplier 2, and Supplier 3 (domestic) from any activities. Next, Scenarios 0, 1, and 2 will be subjected to disruptions with the same durations: 6 weeks, 10 weeks, and 14 weeks, respectively. The simulation is programmed to run a simulation of 251 ticks or days. The baseline data will run for 251 days without any disruptions. The disruption of a 6-week period will entail a 10-week period or 70 ticks without any disruption, then the disruption will apply for 42 ticks. A 10-week disruption will entail a 10-week period without any disruption, then the disruption will apply for 70 ticks. Finally, the 14-week disruption period will have a 10-week period of no disruptions, then the 14 week or 98 tick disruption will apply. The model runs for a total of 251 ticks or 35.85 weeks to ensure that each supply chain recovers from the disruption. Recovery is defined as the amount of time it takes for each supply chain to return to the profit and service level that was computed in the baseline data.

The NetLogo Model Interface gives us the option of choosing the amount of safety stock for a given simulation. The interface also gives us a choice of which scenario to run, and how long the duration of the disruption will be.

Figure 5 shows the simulation interface, highlighting the slider added for safety stock in days, represented by SS_days, where the safety stock can be 0 days of safety stock to 100 days of safety stock. The other highlighted box indicates a drop-down button to select scenario choices, represented by the numbers 0, no disruption; 01, with only supplier 0 closing; 12, with suppliers 1 and 2 closing; and scenario 012, where all three suppliers close. Within the same block, another drop-down button named "breaks" indicates the length of time the disruption will last. A break of 0 indicates no disruption, the number 42 indicates 6 weeks of disruption (42/7=42), a break of 70 indicates a disruption of 10 weeks, and lastly, the number 98 indicates a break of 14 weeks.

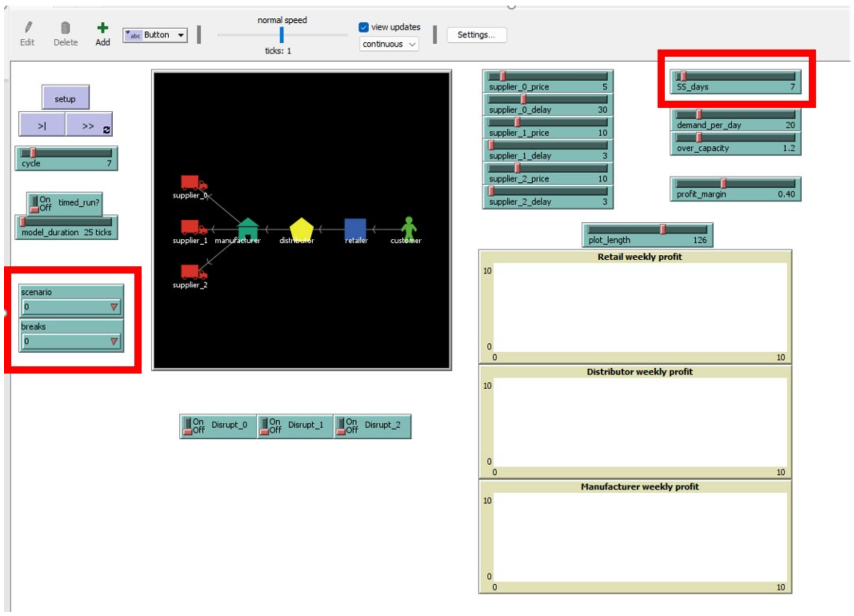

FIGURE 5: NETLOGO SIMULATION INTERFACE HIGHLIGHTING SAFETY STOCK SLIDER, SCENARIO AND BREAKS DROP-DOWN BUTTONS

To understand how the simulation calculates specific variables, there are parameters set. The parameters include the following:

- Demand is held constant at 20 units per day or 140 per week.
- To calculate safety stock, the demand per week held at 140 with 100% safety stock would yield 280 units at each entity except for the suppliers where the total units would be divided by 3 to order the same amount from each supplier. This would yield 93 units at Supplier 0, 93 units at Supplier 1, and 94 units at Supplier 2.
- Each entity can order once a week, on the seventh day.

- All entities have the same lead time of 3 days except for Supplier 0, a global supplier that has a 30-day lead time.

- The capacity of 20% is being utilized at the supplier level only.

- The profit margin is held constant at 40%.

- The cost for the supplier to buy the product is $10 for Supplier 1 and Supplier 2; and $5 for Supplier 0.

- The supply chain is sequential.

- Items are paid for at the time of the order.

Given these parameters, Table 3 was produced using various scenarios with different levels of disruption. The baseline profit was calculated as $34,813.00 and the baseline service level is 98% percent. The 98% calculation is due to the lag in delivery of Supplier 0, which has a lead time of 30 days. At the end of the simulation run, one shipment had not been delivered.

TABLE 3: RETAILER PROFIT AND SERVICE LEVELS WITH DISRUPTIONS OVERVIEW

Retailer Profit and Service Level of Various Supply Chains Under Different Disruptions				
Low-Cost Supply Chain - 7 Days of Safety Stock	**No Disruption**	**AT 6 weeks disruption**	**At 10 Weeks Disruption**	**At 14 Weeks Disruption**
Baseline	$34813, 98%			
Scenario 1 Supplier 0 off		$34813, 98%	$32973, 93%	$30586, 86%
Scenario 2 Supplier 1 and Supplier 2 Off		$34572, 97%	$32185, 90%	$29798, 84%
Scenario 3 All Suppliers Off-Total Disruption		$33208, 93%	$29229, 82%	$25251, 71%
Dual-Purpose Supply Chain - 14 Days Safety Stock				
Baseline	$34813, 98%			
Scenario 1 Supplier 0 off		$34813, 98%	$34813, 98%	$33763, 95%
Scenario 2 Supplier 1 and Supplier 2 Off		$34813, 98%	$34813, 98%	$33698, 95%
Scenario 3 All Suppliers Off-Total Disruption		$34813, 98%	$33222, 93%	$28534, 80%
Customer-Focused Supply Chain 21 Days pf Safety Stock				
Baseline	$34813, 98%			
Scenario 1 Supplier 0 off		$34813, 98%	$34813, 98%	$34813, 98%
Scenario 2 Supplier 1 and Supplier 2 Off		$34813, 98%	$34813, 98%	$34813, 98%
Scenario 3 All Suppliers Off-Total Disruption		$34813, 98%	$34813, 98%	$31525, 81%

In the low-cost supply chain, carrying only 7 days of safety stock (140 units), Scenario 1 at 6 weeks of disruption had no effect on the profit or the service level. However, at 10 weeks disruption, the profit decreased by $1,840 and the service level decreased by 5%. A longer disruption consisting of 14 days, the profit dropped by $4,227 and the service level plummeted by 12%. Scenario 2 had a small impact from the short 6-week disruption and caused profits to start decreasing, albeit only by $241. The service level dropped by only 1 percent. With the longer disruption of 10 weeks, profit dropped by $2,628 and the service level dropped by 8%.

The longest disruption of 14 weeks will have the strongest impact of all other calculations on the chart with a decrease in profits by $9,562 and a drop in service level from 98% to 71%.

The dual-purpose supply chain, holding 14 days of safety stock (280 units), Scenario 1 didn't see a drop in profit or service level at 6 weeks or 10 weeks disruption, but did see a small decrease in profit and service level with the disruption lasting 14 weeks, with the decrease in profit of $1,050 and a 3% decrease in service level. Scenario 2 produced the same results of no change in profits or service level with 6- and 10-week disruption duration, and with the longest duration of 14 weeks, a decrease of $1,115 in profits and a decrease of 3% service level was computed. In the last scenario, 6 weeks of disruption had no impact on profits or service level. With a disruption of 10 weeks, the profit decreased by $1,591 and a 5% decrease in service level. Lastly, a 14-week disruption decreased profits by $6,279 and decreased the service level by 18%.

Our customer-focused supply chain held a safety stock of 21 days (420 units). No impact to the profit or service level was observed until Scenario 3, at the 14-week disruption duration, where profits dropped by $3,288 and the service level dropped by 17%.

4.1 REGRESSION ANALYSIS

To go into further detail on our results, we will subject our simulation to a multitude of runs that include safety stock days from 0 to 30 in 3-day increments, subjecting each day to Scenario 1, 2, and 3. For each simulation run, we will calculate the retailer's profit and service level, given each scenario.

In Scenario 1, when only one supplier is out, the effects are minimal and only occur when the safety stock amount is either at 0 or exceptionally low. Because of this reason, a regression analysis is not necessary. In Figure 6, the profit and service level only decrease when safety stock is at 0 and 3 days.

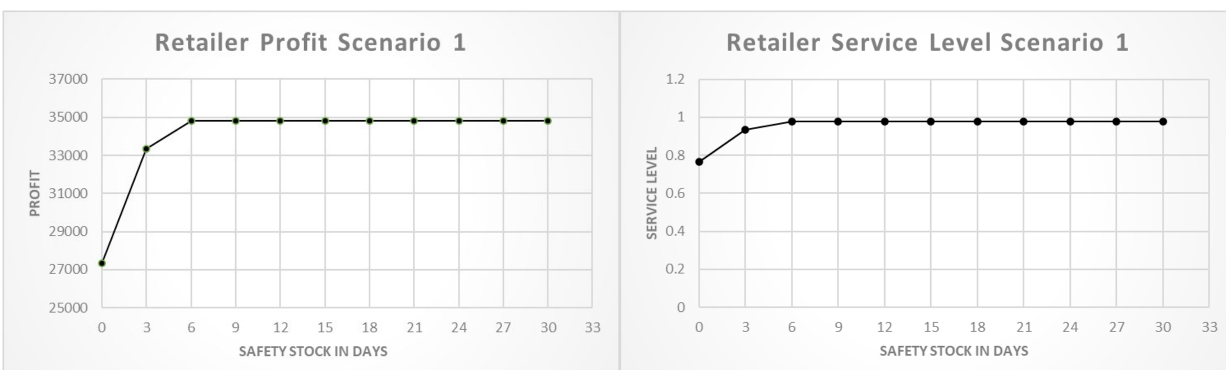

FIGURE 6: SCENARIO 1 RETAILER PROFIT AND SERVICE LEVEL

As shown in Figure 7, in Scenario 2, where Supplier 1 and Supplier 2 are down, both the service level and the profit for the retailer decreased when the safety stock level was at 0 days, 3 days, and 6 days.

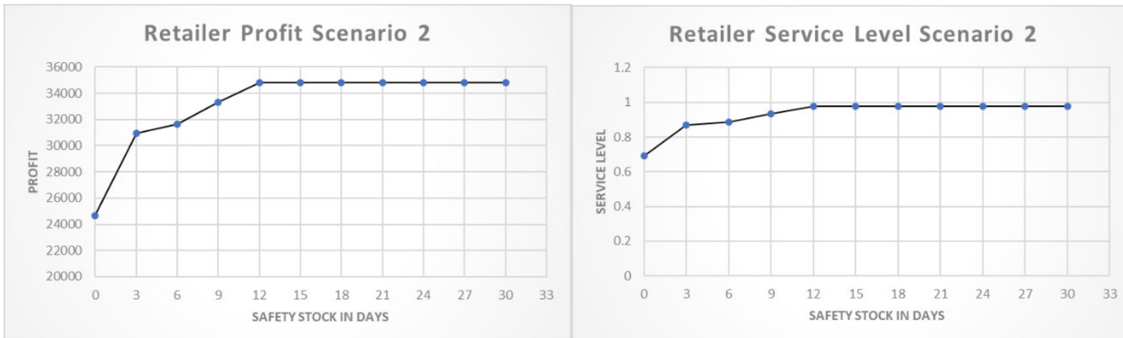

FIGURE 7: SCENARIO 2 RETAILER PROFIT AND SERVICE LEVEL

In the regression analysis in Figure 8 depicts profits for Scenario 2, our independent variable (x-axis) is the safety stock measured in days and our dependent variable (y-axis) is the profit. We want to understand how much of our increase in profit is affected by our days of safety stock. To understand this, we will look at our r-square value, which is .57, means that .57 of our variability in our profit is explained by the safety stock, and our Significance on our f-value and our p-value is much less than our threshold of .05, meaning that there is a statistical significance that states that the increase in safety stock is strongly correlated to our increase in profit. Using our coefficients and our y intercept, our regression equation is equal to 29551 + 237(SS_days). For every unit increase in safety stock, our profits will increase by $237. For this example, we could split the data and run a piecewise regression as well.

RETAIL SCENARIO 2 DATA FOR PROFIT								
Regression Statistics								
Multiple R	0.75611434							
R Square	0.571708896							
Adjusted R Square	0.524120995							
Standard Error	2159.672689							
Observations	11							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	56034342.19	56034342.19	12.01374488	0.007092411			
Residual	9	41977675.12	4664186.124					
Total	10	98012017.31						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	29551.24647	1218.219693	24.2577317	1.64531E-09	26795.44207	32307.05088	26795.44207	32307.05088
SS Days	237.9082715	68.63890381	3.46608495	0.007092411	82.63628361	393.1802594	82.63628361	393.1802594

FIGURE 8: SCENARIO 2 RETAILER PROFIT REGRESSION OUTPUT

In our regression analysis, Figure 9, for the service level for Scenario 2, our independent variable (x-axis) is the safety stock measured in days and our dependent variable (y-axis) is the service level. Like our profit regression analysis, our p-value and f-value both suggest there is a strong correlation between the increase in safety stock and the increase in service levels. Our regression equation is equal to .828 + .0066(SS_days), so for every unit increase in our safety stock, our service level will raise by .0066.

RETAIL SCENARIO 2 DATA FOR SERVICE LEVEL								
Regression Statistics								
Multiple R	0.75611434							
R Square	0.571708896							
Adjusted R Square	0.524120995							
Standard Error	0.060556716							
Observations	11							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0.044055795	0.044055795	12.01374488	0.007092411			
Residual	9	0.033004043	0.003667116					
Total	10	0.077059837						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.828531329	0.034158595	24.2554278 1	1.6467E-09	0.751259219	0.905803439	0.751259219	0.905803439
SS Days	0.006670892	0.001924619	3.46608495	0.007092411	0.002317102	0.011024682	0.002317102	0.011024682

FIGURE 9: SCENARIO 2 RETAILER SERVICE LEVEL REGRESSION OUTPUT

Scenario 3 with total disruption yielded a decrease in both profit and service level for the duration of the simulation. In Figure 10, the service level at 0 safety stock days returned a service level of only 52% and profits decreased from our baseline amount from $34, 813 to only $18,616.

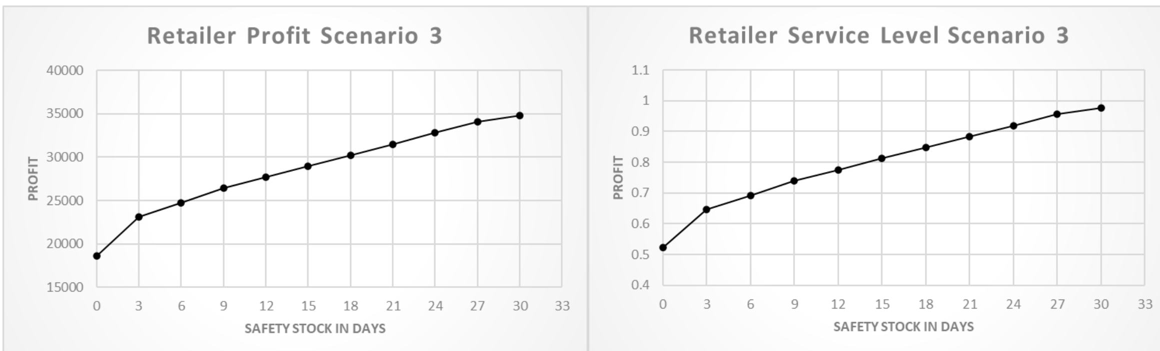

FIGURE 10: SCENARIO 3 RETAILER PROFIT AND SERVICE LEVEL

Our regression analysis for Scenario 3, Figure 11 for the retailer's profit has an even stronger correlation with the p-value of 1.16117E-07. The r-square in this regression states that 96% of our variability in our profit is explained by the safety stock. Our regression equation is 21083 + 491(SS_days). For every unit increase in safety stock, our profits will increase by $491.

RETAIL SCENARIO 3 DATA FOR PROFIT

Regression Statistics	
Multiple R	0.980454823
R Square	0.961291661
Adjusted R Square	0.956990734
Standard Error	1033.510285
Observations	11

ANOVA

	df	SS	MS	F	Significance F
Regression	1	238738659.8	238738659.8	223.5080377	1.16117E-07
Residual	9	9613291.589	1068143.51		
Total	10	248351951.4			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	21083.4105	582.978425	36.16499273	4.67833E-11	19764.62168	22402.19932	19764.62168	22402.19932
SS Days	491.0704241	32.84711309	14.95018521	1.16117E-07	416.765092	565.3757563	416.765092	565.3757563

FIGURE 11: SCENARIO RETAILER PROFIT REGRESSION OUTPUT

Our regression output for the retailer's service level under the conditions of Scenario 3 is remarkably like our profit output as depicted in Figure 12. The p-values and f-value prove there is a strong correlation between the service level and the amount of safety stock. Our regression equation is equal to .59 + .013 (SS_days). For every unit increase in safety stock, our service level will go up by .013.

RETAIL SCENARIO 3 DATA FOR SERVICE LEVEL								
Regression Statistics								
Multiple R	0.980458924							
R Square	0.961299702							
Adjusted R Square	0.956999669							
Standard Error	0.028975552							
Observations	11							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0.187694027	0.187694027	223.5563471	1.16008E-07			
Residual	9	0.007556244	0.000839583					
Total	10	0.19525027						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.591090185	0.016344416	36.16465654	4.67872E-11	0.554116547	0.628063822	0.554116547	0.628063822
SS Days	0.013769166	0.000920904	14.9518008	1.16008E-07	0.011685937	0.015852394	0.011685937	0.015852394

FIGURE 12: SCENARIO 3 RETAILER SERVICE LEVEL REGRESSION OUTPUT

For an overview of how profit is affected by days of safety stock, Figure 13 shows each scenario with the safety stock in days and the profit for each data point. In the figure, the blue line depicts Scenario 1. The red line depicts Scenario 2, and the black line depicts Scenario 3. All scenarios level out at the eleven-day mark, with Scenario 1 and 2 leveling out at the five-day mark.

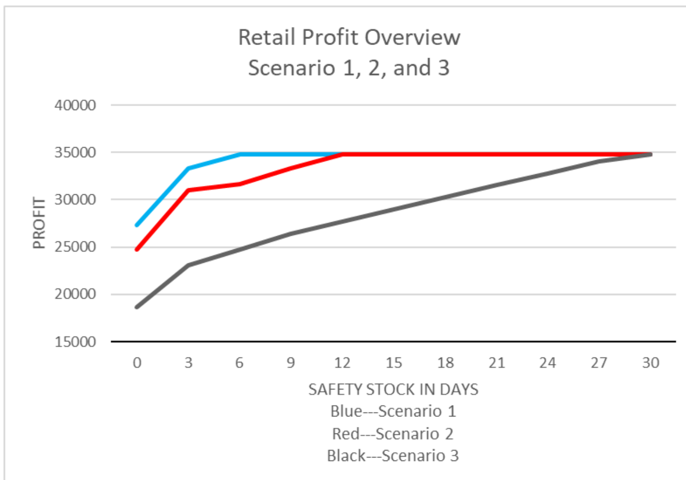

FIGURE 13: RETAILER PROFIT OVERVIEW WITH SCENARIO 1, 2, AND 3

In Figure 14, we have an overview of the service level with each increment of safety stock. The blue line depicts the data for Scenario 1, the red line depicts the data for Scenario 2, and the black line depicts the data for Scenario 3. The data for the service levels as a function of safety stock moves like the data for profits as a function of safety stock in that the more safety stock a company holds, service levels and profits will be higher.

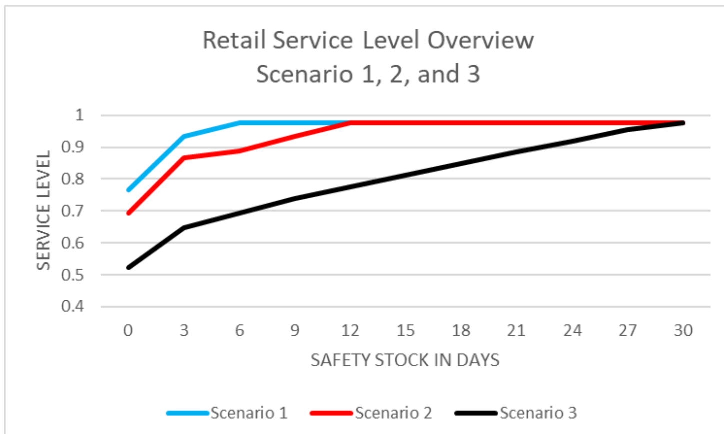

FIGURE 14: RETAILER SERVICE LEVEL OVERVIEW WITH SCENARIO 1, 2, AND 3

With this information, we can infer that having a low level of safety stock can decrease the profit and the service levels significantly. With the information from this study, we can understand why Just-In-Time (JIT) may not be an effective way to operate a supply chain. When we look at the implications of JIT, we assume a cost decrease due to lower holding costs; however, in a study conducted by Moussawi-Haidar, et al. 2021, the costs of stockouts due to disruptions are large as well. In the study. Moussawi-Haidar suggested having a buffer stock to ensure product availability in case of disruptions, as well as a JIT inventory plan to quickly replenish inventory in case of a major disruption. Essentially, the management decision of both safety stock and a

JIT plan in place would be optimal, but often there are disruptions that cause all suppliers to shut down making a JIT inventory plan not feasible. Covid-19 has understandably caused supply chain managers to rethink their decisions for inventory. Our conclusions in regard to safety stock and JIT ultimately proves that JIT causes vulnerabilities within the supply chain when there are major disruptions within the supply chain. We can see that from our results that the profit decrease is not substantially detrimental; however, in order to maintain profitability during a crisis, safety stock plays an integral part.

Another point to note is that while analyzing the data between safety stock amount in days and each scenario, Scenario 1 dictates that supplier 0, the global supplier is no longer able to produce, Scenario 2 dictates that supplier 1 and 2 can no longer supply, and Scenario 3, no suppliers can supply product, in Scenario 1 and 2, both supply chains recovered quickly and at the same amount of safety stock of 12 days, proving that no matter where the product was produced, either domestically or globally, the outcome of when the supply chain regained normal operations was the same. In Scenario 3, no matter the location, because all three suppliers were unable to supply, 30 days of safety stock was optimal to regain normal operations.

While we are examining different parameters of the supply chain, we increased the holding cost to 40%, double the previous amount in our scenarios. For this analysis, we used only Scenario 3 with a duration of 14 days disruption. In Figure 15, the profit and service level are moving in unison. We observe that the increase in holding costs does not affect the service level because selling more products dominates.

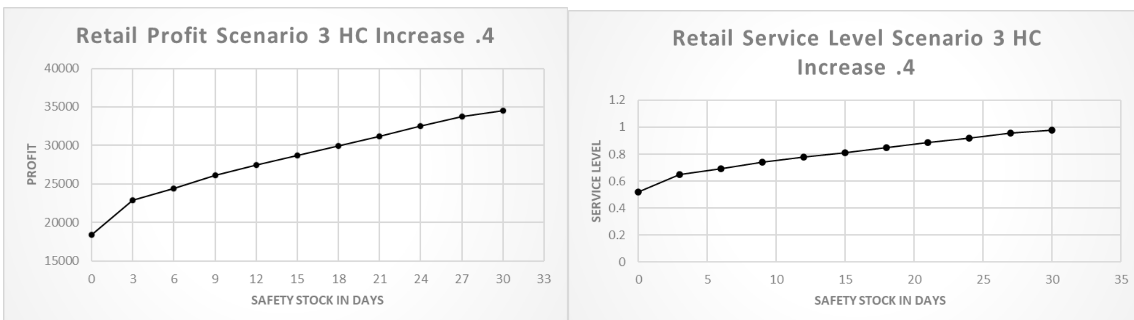

FIGURE 15: SCENARIO 3 RETAILER HOLDING COST INCREASE

Our next analysis is depicted below in Table 4. Capacity is a managerial decision that can affect the resiliency of a supply chain. Below we examine one scenario, Scenario 1, where supplier 0 is turned off. We look at the capacities of all suppliers as 100% at capacity, 20% over capacity, and 40% over capacity, respectively. The low-cost supply chain with 7-day safety stock could not obtain higher than an 85% service rate, even with 40% over capacity. The baseline profit and service level are $34813, and 98%. The baseline profit and service level are calculated with 21-day safety stock, and 20% over capacity. Given these values, a decrease in profit occurred at capacity level 100%, 20% over capacity, and 40% over capacity in the amounts of $11,963, $6,436, and $4596, and a decrease in service level occurred from 98% to 64% with 100% capacity, 98% to 80% with 20% over capacity, and 98% to 85% with 40% over capacity. The same values are present for the low-cost supply chain without any disruption for each level of capacity.

We analyze the dual-purpose supply chain next with no disruption causing a decrease in profits of $8979 with only 100% capacity. With 20% over capacity, we have a decrease in profits of $2472 and with 40% over capacity, we lose only $ 632 and dropped in service level by only 16%. When incorporating Scenario 1, we have a decrease in profit of $6763 and a decrease in service level from 98% to 79%. With 20% over capacity, the profits drop by only $1114, and the service level drops by 4%. Lastly, with 40% over capacity, profits decrease by $632 with a service level of 95%.

With 21 days of safety stock, the customer-focused supply chain only felt the effect of the disruption with a decrease in profit of $3772 and a decrease in service level to 87%.

TABLE 4: RETAILER PROFIT AND SERVICE LEVELS WITH CAPACITY LEVELS OF 100% AT CAPACITY, 20%, AND 40% OVER CAPACITY

Retail Profit and Service Level of Various Supply Chains with Supplier Capacity Levels			
SCENARIO 1			
Low-Cost Supply Chain - 7 Days of Safety Stock	**100% Capacity**	**20% Over Capacity**	**40% over Capacity**
Baseline - No Disruption	$22850, 64%	$28377, 80%	$30217, 85%
Scenario 2 - Supplier 1 and Supplier 2 Off	$22850, 64%	$28377, 80%	$30217, 85%
Dual-Purpose Supply Chain - 14 Days Safety Stock			
Baseline	$25834, 72%	$32341, 91%	$34181, 96%
Scenario 2 Supplier 1 and Supplier 2 Off	$28050, 79%	$33699, 94%	$34046, 95%
Customer-Focused Supply Chain 21 Days pf Safety Stock			
Baseline	$34813, 98%	$34813, 98%	$34813, 98%
Scenario 2 Supplier 1 and Supplier 2 Off	$24385, 68%	$34813, 98%	$34813, 98%

Another key factor of service levels and profitability includes the lead times of the suppliers. For this study, we analyzed the various scenarios with various lead times within the NetLogo model. We subjected Scenario 1, 2, and 3 to the different lead times of the suppliers and the duration for the disruption was set for 14 weeks for each scenario. The first variation of lead times gave Supplier 0, a global supplier, a lead time of 15 days and the other two suppliers, 1 and 2, a lead time of 1 day each. The second variation gave the suppliers the same lead time we have using for the model for all data, 30 days for Supplier, and 3 days for each of the domestic suppliers, 1 and 2. We added two more variations with lead times of 60 days for Supplier 0 and 10 days for Suppliers 1 and 2. The last variation of lead times gave Supplier 0 a lead time of 90 days, and Suppliers 1 and 2 a lead time of 20 days. To understand the longer lead times given for variations

3 and 4, we must remember the recent pandemic where major disruptions occurred for transit times all over the world.

Figure 16 shows us a summary of how profits and the service level in Scenario 1 were affected with each lead time variation. For lead times 15-1-1 and 30-3-3, there were no differences in profit and service level; however, for lead times 60-10-10 and 90-20-20, there was a significant drop in both profit for a total of $2,259 and service level of approximately 6%.

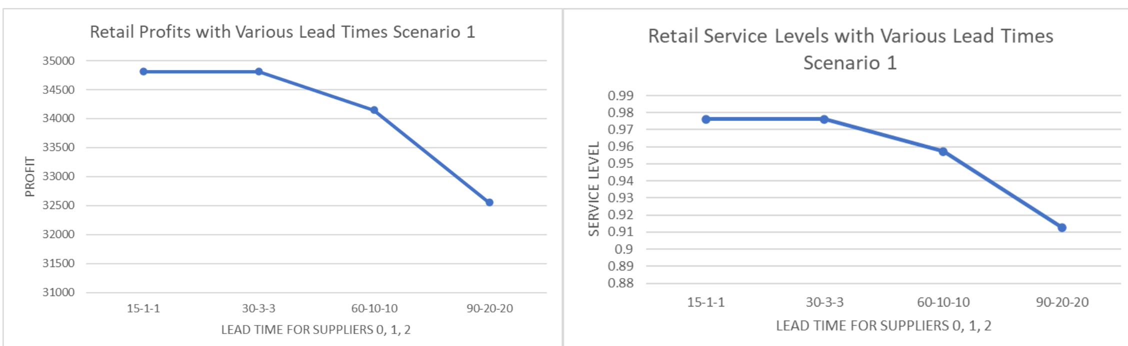

FIGURE 16: RETAILER PROFITS AND SERVICE LEVELS DURING VARIOUS LEAD TIMES IN SCENARIO 1

In Scenario 2, profits and service levels drop similarly as depicted in Figure 17. However, in Scenario 1 the service level drops from 97% to 91% and in Scenario 2 the service level drops from 90% to 79% creating a wider gap in the level of service. Profits also drop by $4,134, creating a wider gap as well.

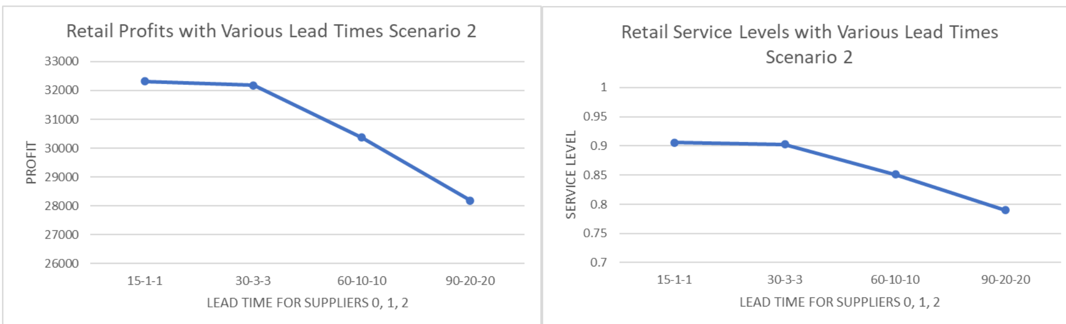

FIGURE 17: RETAILER PROFITS AND SERVICE LEVELS DURING VARIOUS LEAD TIMES IN SCENARIO 2

Lastly, in Scenario 3, as shown in Figure 18, the data shows another downward trend as the service levels and profits decrease. In this scenario, the profits drop by $2,927 and the service level drops by approximately 8%. With this analysis, we can see that having lead times that are longer than normal can create decreases in profit as well as service levels, and the 60-10-10 shows a larger overall decrease in profits and service level; however, the last lead time variance coupled with Scenario 3 creates the lowest profit and service level among all lead time variations and scenarios.

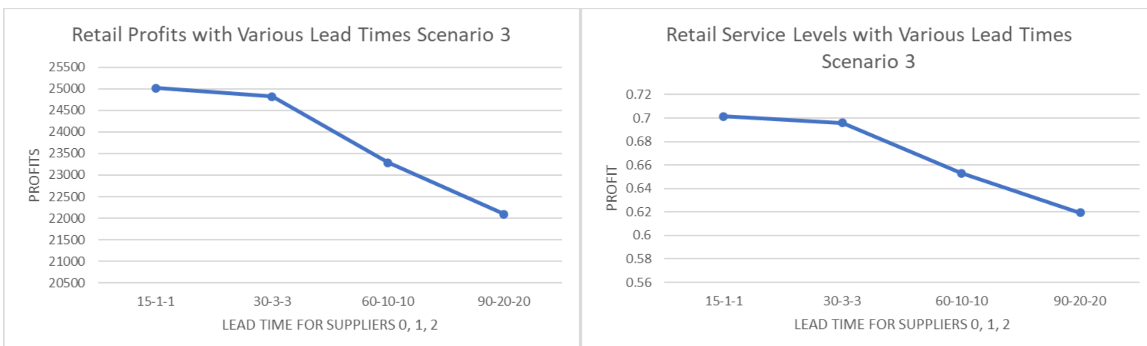

FIGURE 18: RETAILER PROFITS AND SERVICE LEVELS DURING VARIOUS LEAD TIMES IN SCENARIO 3

Next, we analyze the service level of panic buying during a Scenario 1 disruption, meaning that the global supplier has shut down. Panic buying was an action that was prominent during the pandemic (Chua, et al., 2021). To understand how panic buying could affect service levels, we increased the demand during the 14-week duration period. For each 7-day cycle time, the demand increased by 5%. In Figure 19, we can see how the service level went from 95% down to 50% within the 14-week disruption duration. Because of the previous data analyzed, we know that profits dropped similarly.

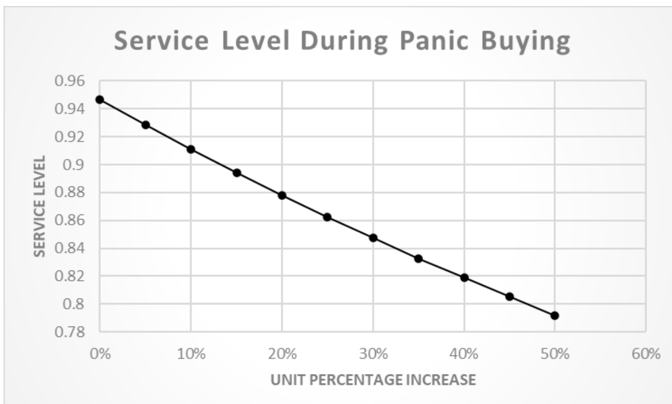

FIGURE 19: RETAILER SERVICE LEVEL DURING PANIC BUYING SCENARIO 1

CHAPTER 5: LIMITATIONS, CONCLUSIONS, AND FUTURE RESEARCH

Supply chain management literature on resiliency is vast; however, the supply chain industry has never encountered a disruption like the Covid-19 pandemic. Quickly, supply chains all over the world were experiencing shortages, longer lead times, decreases in profits, and lower service levels. Our research analyzes specific managerial decisions to mitigate some of the disruption risks by reproducing various disruption scenarios and durations within an agent-based model simulation.

5.1 LIMITATIONS

Agent-based modeling simulations have been used for many purposes due to the simulation's ability to model agents who can learn, interact, and change due to other agents or due to the environment around them. However, there are certain limiting factors that are present in our model. Our limitations include the parameters set within the simulation. These parameters were set throughout the entire supply chain and include equal cycle time, the same holding costs, constant demand at 20 units per day, and the supply chain was successive. While we did not have real data to construct our parameters, a sensitivity analysis and calibration was conducted to use the best numerical values for the model. Neither agent, suppliers, manufacturers, distributors, or retailers could raise their prices as we used a cost-plus pricing model. We assume perfect quality with no reverse logistics. Backorders were not configured into the model and items were paid for at the time of the order. NetLogo is a great simulation tool; however, to code the agents and their properties can become very complicated. To code the original generic supply chain would have taken us years, thus the initial model to fit within the timeframe of a dissertation was coded and simulated.

5.2 CONCLUSIONS

We looked at various safety stock to keep the service levels as high as possible, and to keep profit at a steady increase as product delivery allowed. We analyzed differences in 3 different supply chains with different end goals for the customer, including a low cost supply chain, a dual purpose supply chain and a customer focused supply chain. Each supply chain was subjected to different scenarios as well as different durations in the disruption as programed in our simulation. We explored different holding costs, capacity increases at the supplier level, and watched the behavior of panic buying. Lastly, we subjected the supply chain to different lead times to analyze how the supply chain was affected. For each managerial decision, we quantified the outcome by measuring the decrease in profitability and the decrease in service level. The results concluded that when subjecting the three types of supply chain to different disruptions and durations of the disruptions, the low cost supply chain, only carrying 7 days of safety stock had decrease in profit of 32% and a decrease in service level of 27% with Scenario 3, and a duration of 14 weeks disruption. The customer focused supply chain holding 21 days of safety stock had a profit decrease of 10% and a service level decrease of 17%, much lower than the low cost supply chain.

When running regression analysis on supply chains subjected to Scenario 1, 2, and 3, all regressions showed a strong correlation between the level of safety stock and the profit and service level, meaning that the more safety stock that an entity held, the less the supply chain suffered losses in profit and in service levels. Scenario 1 and 2 maintained a normal profit and service level while Scenario 3 did not hold enough stock to maintain either unless the retailer carried 30 days of safety stock.

Holding costs were analyzed in the simulation. When increasing the holding cost from 20% to 40%, we saw no difference in the service level as the sell of the product dominates any increase in the holding costs.

Managerial decisions on the capacity ranging from 100% capacity to 20% over capacity, then 40% over capacity of the suppliers were analyzed with profit decreases and service level decreases computed for Scenario 1 and for each type of supply chain. The low cost supply chain suffered the most in profitability and in service levels with 100% capacity, decreasing in profitability by 41% and a service level decrease of 34%. With a customer focused supply chain holding more safety stock, profitability still dropped 35% and the service level dropped by 30%.

Lead times sometimes cannot be controlled; however, buying on a global level or domestically can help. In our study, we subjected each supply chain type to various lead times, while applying each scenario to the model for the disruption duration of 14 days. When the supply chain had lead times of more than 30 days at the global level and more than 3 days at the domestic level, profits and service level declined significantly over all to show a decrease in profitability of 45% and a decrease in service level of 36%.

Panic buying happened during the pandemic, so our study also investigated the impact of service levels for a low cost supply chain, holding only 7 days safety stock to the 14 week disruption duration, with Scenario 1. We increased the unit demanded during the disruption period only and ran the model for each 5% increase to the demand. With a 10% increase in demand, the service level dropped to approximately 91% and with a 50% increase in demand, the profit level dropped to approximately 79%.

Our analysis focuses heavily on safety stock, capacity, and lead times of the supply chain; all attributes that can be navigated through supply chain management decision making. Our hope is to help guide managerial decisions in the future to help mitigate disruptions and have resilient supply chains given this analysis.

5.3 FUTURE RESEARCH

Because agent-based models have such vast capabilities, the research possibilities are abundant. With the initial model already built, we can add more agents functioning within the supply chain to test different theories for managerial decisions. While expanding the model, we can also create new networks within the supply chain and test different connectivity, such as multiple echelons in various locations. The number of limitations for the initial model can be reduced as part of our future research. Reduction of the limitations will allow us to make the supply chain more realistic. Testing other theories for managerial decisions can be executed including game theory pricing, backstock logging, and quality issues involving the reverse supply chain. Also, within our future research, we would like to have data to set the parameters of the supply chain so that we are able to test the simulation against a real-world scenario. Lastly, the parameters for disruptions can be set to recreate how specific disruptions and the time frame in which durations can last.

WORKS CITED

Achmad, Audi Luqmanul, et al. "Designing a Food Supply Chain Strategy during COVID-19 Pandemic Using an Integrated Agent-Based Modelling and Robust Optimization." Heliyon, vol. 7, no. 11, 2021, https://doi.org/10.1016/j.heliyon.2021.e08448.

Adhitya, Arief, et al. "Supply Chain Risk Identification Using a HAZOP-Based Approach." *AIChE Journal*, vol. 55, no. 6, 28 Apr. 2009, pp. 1447–1463., https://doi.org/10.1002/aic.11764.

Ang, Erjie, et al. "Disruption Risk and Optimal Sourcing in Multitier Supply Networks." *Management Science*, vol. 63, no. 8, 14 July 2016, pp. 2397–2419., https://doi.org/10.1287/mnsc.2016.2471.

Asgary, A., Najafabadi, M. M., Karsseboom, R., & Wu, J. (2020, November). A drive-through simulation tool for mass vaccination during COVID-19 pandemic. In *Healthcare* (Vol. 8, No. 4, p. 469). MDPI. https://doi.org/10.1287/mnsc.2016.2471.

Behzadi, Golnar, et al. "On Metrics for Supply Chain Resilience." *European Journal of Operational Research*, vol. 287, no. 1, May 2020, pp. 145–158., https://doi.org/10.1016/j.ejor.2020.04.040.

Belhadi, Amine, et al. "Manufacturing and Service Supply Chain Resilience to the COVID-19 Outbreak: Lessons Learned from the Automobile and Airline Industries." *Technological Forecasting and Social Change*, vol. 163, Feb. 2021, https://doi.org/https://doi.org/10.1016/j.techfore.2020.120447.

Bier, Tobias, et al. “Methods for Mitigating Disruptions in Complex Supply Chain Structures: A Systematic Literature Review.” *International Journal of Production Research*, vol. 58, no. 6, 22 Nov. 2019, pp. 1835–1856., https://doi.org/10.1080/00207543.2019.1687954.

Blackhurst, Jennifer, et al. “An Empirically Derived Framework of Global Supply Resiliency.” *Journal of Business Logistics*, vol. 32, no. 4, 6 Dec. 2011, pp. 374–391., https://doi.org/10.1111/j.0000-0000.2011.01032.x.

Cao, Yunzhi, et al. “Data-Driven Wasserstein Distributionally Robust Mitigation and Recovery against Random Supply Chain Disruption.” *Transportation Research Part E: Logistics and Transportation Review*, vol. 163, 2022, p. 102751., https://doi.org/10.1016/j.tre.2022.102751.

Carvalho, Helena, et al. “Supply Chain Redesign for Resilience Using Simulation.” Computers & Industrial Engineering, vol. 62, no. 1, 2012, pp. 329–341., https://doi.org/10.1016/j.cie.2011.10.003.

Chopra, Sunil, and ManMohan S. Sodhi. “Risk Conduction of Supply Chain Disruptions.” *Managing Risk of Supply Chain Disruptions*, 16 Mar. 2014, pp. 28–58., https://doi.org/10.4324/9781315776910-7.

Chua, Grace, et al. “The Determinants of Panic Buying during COVID-19.” International Journal of Environmental Research and Public Health, vol. 18, no. 6, 21 Mar. 2021, p. 3247., https://doi.org/10.3390/ijerph18063247.

Colon, Célian, et al. "Criticality Analysis of a Country's Transport Network via an Agent-Based Supply Chain Model." *Nature Sustainability*, vol. 4, no. 3, 2020, pp. 209–215., https://doi.org/10.1038/s41893-020-00649-4.

Craighead[1], Christopher W., et al. "The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities." *Decision Sciences*, vol. 38, no. 1, 27 Mar. 2007, pp. 131–156., https://doi.org/10.1111/j.1540-5915.2007.00151.x.

Craighead[2], Christopher W., et al. "Pandemics and Supply Chain Management Research: Toward a Theoretical Toolbox*." *Decision Sciences*, vol. 51, no. 4, 2020, pp. 838–866., https://doi.org/10.1111/deci.12468.

Cuevas, Erik. "An Agent-Based Model to Evaluate the COVID-19 Transmission Risks in Facilities." *Computers in Biology and Medicine*, vol. 121, 2020, p. 103827., https://doi.org/10.1016/j.compbiomed.2020.103827.

Delcea, Camelia, et al. "An Agent-Based Modeling Approach to Collaborative Classrooms Evacuation Process." *Safety Science*, vol. 121, 2020, pp. 414–429., https://doi.org/10.1016/j.ssci.2019.09.026.

Ding, Can, et al. "Role of Distribution Centers Disruptions in New Retail Supply Chain: An Analysis Experiment." *Sustainability*, vol. 14, no. 11, 2022, p. 6529., https://doi.org/10.3390/su14116529.

Dorigatti, Mariana, et al. “A Service-Oriented Framework for Agent-Based Simulations of Collaborative Supply Chains.” Computers in Industry, vol. 83, 2016, pp. 92–107., https://doi.org/10.1016/j.compind.2016.09.005.

Dulam, Rithika, et al. “Development of an Agent-Based Model for the Analysis of the Effect of Consumer Panic Buying on Supply Chain Disruption Due to a Disaster.” *Journal of Advanced Simulation in Science and Engineering*, vol. 7, no. 1, 2020, pp. 102–116., https://doi.org/10.15748/jasse.7.102.

Fan, Yingjie, et al. “Catastrophe Insurance and Flexible Planning for Supply Chain Disruption Management: A Stochastic Simulation Case Study.” *International Journal of Production Research*, 2023, pp. 1–18., https://doi.org/10.1080/00207543.2023.2176179.

Ghadge, Abhijeet, et al. “Impact of Financial Risk on Supply Chains: A Manufacturer-Supplier Relational Perspective.” *International Journal of Production Research*, vol. 59, no. 23, 2020, pp. 7090–7105., https://doi.org/10.1080/00207543.2020.1834638.

Graves, Stephen C., and Sean P. Willems. “Supply Chain Design: Safety Stock Placement and Supply Chain Configuration.” *Supply Chain Management: Design, Coordination and Operation*, 2003, pp. 95–132., https://doi.org/10.1016/s0927-0507(03)11003-1.

Grossman, Gene, and Elhanan Helpman. “When Tariffs Disturb Global Supply Chains.” *National Bureau of Economic Research*, Aug. 2020, https://doi.org/10.3386/w27722.

Hammami, Ramzi, et al. “Government Strategies to Secure the Supply of Medical Products in Pandemic Times.” *European Journal of Operational Research*, vol. 306, no. 3, 2023, pp. 1364–1387., https://doi.org/10.1016/j.ejor.2022.07.007.

He, Jian, et al. “A Real-Option Approach to Mitigate Disruption Risk in the Supply Chain.” *Omega*, vol. 88, 2019, pp. 133–149., https://doi.org/10.1016/j.omega.2018.08.008.

Helbing, Dirk. “Agent-Based Modeling.” Understanding Complex Systems, 10 Feb. 2012, pp. 25–70., https://doi.org/10.1007/978-3-642-24004-1_2.

Ivanov, Dmitry, and Alexandre Dolgui. “OR-Methods for Coping with the Ripple Effect in Supply Chains during COVID-19 Pandemic: Managerial Insights and Research Implications.” *International Journal of Production Economics*, vol. 232, 15 Sept. 2020, p. 107921., https://doi.org/10.1016/j.ijpe.2020.107921.

Kaur, Navroop, and Harjot Kaur. “A Multi-Agent Based Evacuation Planning for Disaster Management: A Narrative Review.” *Archives of Computational Methods in Engineering*, vol. 29, no. 6, 2022, pp. 4085–4113., https://doi.org/10.1007/s11831-022-09729-4.

Khouja, Moutaz, and Ramzi Hammami. “Building Viable Stockpiles of Personnel Protective Equipment.” *European Journal of Operational Research*, vol. 307, no. 3, 2023, pp. 1206–1224., https://doi.org/10.1016/j.ejor.2022.10.004.

Kim, Karl, et al. “An Agent-Based Model of Short-Notice Tsunami Evacuation in Waikiki, Hawaii.” *Transportation Research Part D: Transport and Environment*, vol. 105, 2022, p. 103239., https://doi.org/10.1016/j.trd.2022.103239.

Korpela, Jukka, et al. “Customer Service Based Design of the Supply Chain.” *International Journal of Production Economics*, vol. 69, no. 2, 25 Jan. 2001, pp. 193–204., https://doi.org/10.1016/s0925-5273(00)00062-1.

Lambert, Douglas M, and Martha C Cooper. “Issues in Supply Chain Management.” *Industrial Marketing Management*, vol. 29, no. 1, Jan. 2000, pp. 65–83., https://doi.org/10.1016/s0019-8501(99)00113-3.

Lau, J.S.K., et al. “Agent-Based Modeling of Supply Chains for Distributed Scheduling.” IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 36, no. 5, 2006, pp. 847–861., https://doi.org/10.1109/tsmca.2005.854231.

Li, Jing, and Felix T.S. Chan. “An Agent-Based Model of Supply Chains with Dynamic Structures.” *Applied Mathematical Modelling*, vol. 37, no. 7, 2013, pp. 5403–5413., https://doi.org/10.1016/j.apm.2012.10.054.

Li, Qingfeng, and Yajing Huang. “Optimizing Global Covid-19 Vaccine Allocation: An Agent-Based Computational Model of 148 Countries.” *PLOS Computational Biology*, vol. 18, no. 9, 2022, https://doi.org/10.1371/journal.pcbi.1010463.

Liu, Ming, et al. “An Optimization Approach for Multi-Echelon Supply Chain Viability with Disruption Risk Minimization.” *Omega*, vol. 112, 2022, p. 102683., https://doi.org/10.1016/j.omega.2022.102683.

Lohmer, Jacob, et al. “Analysis of Resilience Strategies and Ripple Effect in Blockchain-Coordinated Supply Chains: An Agent-Based Simulation Study.” International Journal of Production Economics, vol. 228, 2020, p. 107882., https://doi.org/10.1016/j.ijpe.2020.107882.

Lummus, Rhonda R., and Robert J. Vokurka. “Defining Supply Chain Management: A Historical Perspective and Practical Guidelines.” *Industrial Management & Data Systems*, vol. 99, no. 1, 1999, pp. 11–17., https://doi.org/10.1108/02635579910243851.

Macal, Charles M., and Michael J. North. “Agent-Based Modeling and Simulation.” *Proceedings of the 2009 Winter Simulation Conference (WSC)*, 13 Dec. 2009, https://doi.org/10.1109/wsc.2009.5429318.

Maidstone, Robert. (2012). Discrete Event Simulation, System Dynamics and Agent Based Simulation: Discussion and Comparison. 1-6. Mena, Carlos, et al. “Toward a Theory of Multi-Tier Supply Chain Management.” *Journal of Supply Chain Management*, vol. 49, no. 2, 16 Apr. 2013, pp. 58–77., https://doi.org/10.1111/jscm.12003.

Mentzer, John T., et al. “Defining Supply Chain Management.” *Journal of Business Logistics*, vol. 22, no. 2, 10 May 2011, pp. 1–25., https://doi.org/10.1002/j.2158-1592.2001.tb00001.x.

Messina, Dario, et al. “An Information Management Approach for Supply Chain Disruption Recovery.” *The International Journal of Logistics Management*, Emerald Publishing Limited, 6 Aug. 2020, https://www.emerald.com/insight/content/doi/10.1108/IJLM-11-2018-0294/full/html.

Moussawi-Haidar, Lama, et al. “Joint Reserve Stock and Just-in-Time Inventory under Regular Preventive Maintenance and Random Disruptions.” *International Journal of Production Research*, vol. 60, no. 5, 2021, pp. 1666–1687., https://doi.org/10.1080/00207543.2020.1868596.

Na, Hyeong Suk, and Amarnath Banerjee. “Agent-Based Discrete-Event Simulation Model for No-Notice Natural Disaster Evacuation Planning.” *Computers & Industrial Engineering*, vol. 129, 2019, pp. 44–55., https://doi.org/10.1016/j.cie.2019.01.022.

Naqvi, Asjad, and Irene Monasterolo. “Assessing the Cascading Impacts of Natural Disasters in a Multi-Layer Behavioral Network Framework.” *Scientific Reports*, vol. 11, no. 1, 2021, https://doi.org/10.1038/s41598-021-99343-4.

Ni, Ni, et al. “Modeling the Impact of Unmet Demand in Supply Chain Resiliency Planning.” *Omega*, vol. 81, Dec. 2018, pp. 1–16., https://doi.org/10.1016/j.omega.2017.08.019. Fpau

Nie, Jing, et al. “Simulation Study on Network Stability of Short Cycle Product Supply Chain Based on Netlogo.” *CICTP 2018*, 5 July 2018, https://doi.org/10.1061/9780784481523.041.

Parmigiani, Anne, et al. “Efficiency Meets Accountability: Performance Implications of Supply Chain Configuration, Control, and Capabilities⋆.” *Journal of Operations Management*, vol. 29, no. 3, 2011, pp. 212–223., https://doi.org/10.1016/j.jom.2011.01.001.

Pournader[1], Mehrdokht , et al. “A Review of the Existing and Emerging Topics in the Supply Chain Risk Management Literature.” *Decision Sciences*, vol. 51, no. 4, 15 Aug. 2020, pp. 867–919., https://doi.org/10.1111/deci.12470.

Rahman[1], Md Mamunur, et al. “Multi-Level Impacts of Climate Change and Supply Disruption Events on a Potato Supply Chain: An Agent-Based Modeling Approach.” Agricultural Systems, vol. 201, 2022, p. 103469., https://doi.org/10.1016/j.agsy.2022.103469.

Rahman[2], T., Taghikhah, F., Paul, S. K., Shukla, N., and Agarwal, R. “An Agent-Based Model for Supply Chain Recovery in the Wake of the Covid-19 Pandemic.” *Computers & Industrial Engineering*, vol. 158, Aug. 2021, https://doi.org/10.1016/j.cie.2021.107401.

Rahman[3], Towfique, et al. “Managing Panic Buying-Related Instabilities in Supply Chains: A Covid-19 Pandemic Perspective.” *IFAC-PapersOnLine*, vol. 55, no. 10, 2022, pp. 305–310., https://doi.org/10.1016/j.ifacol.2022.09.405.

Riddle, Matthew E., et al. “Agent-Based Modeling of Supply Disruptions in the Global Rare Earths Market.” *Resources, Conservation and Recycling*, vol. 164, Jan. 2021, https://doi.org/10.1016/j.resconrec.2020.105193.

Sawik, Tadeusz. “A Stochastic Optimisation Approach to Maintain Supply Chain Viability under the Ripple Effect.” *International Journal of Production Research*, vol. 61, no. 8, 2023, pp. 2452–2469., https://doi.org/10.1080/00207543.2023.2172964.

Shamil, Md. Salman, et al. “An Agent Based Modeling of Covid-19: Validation, Analysis, and Recommendations.” *Cognitive Computation*, 2020, pp. 1–12., https://doi.org/10.1101/2020.07.05.20146977.

Shen, Bin, and Qingying Li. “Market Disruptions in Supply Chains: A Review of Operational Models.” *International Transactions in Operational Research*, vol. 24, no. 4, 12 June 2016, pp. 697–711., https://doi.org/10.1111/itor.12333.

Singh, Chandra Shekhar, et al. “Performance Indicators for Supply Chain Resilience: Review and Conceptual Framework.” *Journal of Industrial Engineering International*, vol. 15, no. S1, 2019, pp. 105–117., https://doi.org/10.1007/s40092-019-00322-2.

Snyder, Lawrence V., et al. “Or/MS Models for Supply Chain Disruptions: A Review.” *IIE Transactions*, vol. 48, no. 2, 2015, pp. 89–109., https://doi.org/10.1080/0740817x.2015.1067735.

Tisue, Seth, and Uri Wileksky. *NetLogo: A Simple Environment for Modeling Complexity*, 16 May 2004, http://ccl.sesp.northwestern.edu/papers/netlogo-iccs2004.pdf.

Wong, Christina W.Y., et al. “Supply Chain and External Conditions under Which Supply Chain Resilience Pays: An Organizational Information Processing Theorization.” *International Journal of Production Economics*, vol. 226, Aug. 2020, p. 107610., https://doi.org/10.1016/j.ijpe.2019.107610.

Wu, Teresa, et al. “Supply Chain Risk Management: An Agent-Based Simulation to Study the Impact of Retail Stockouts.” *IEEE Transactions on Engineering Management*, vol. 60, no. 4, Nov. 2013, pp. 676–686., https://doi.org/10.1109/tem.2012.2190986.

Upton E, and Nuttall W. Fuel panics: insights from spatial agent-based simulation. *IEEE Transactions on Intelligent Transport Systems.* (2014) 15:1499–509. doi: 10.1109/TITS.2014.2302358

Ying, Fabian, and Neave O'Clery. "Modelling Covid-19 Transmission in Supermarkets Using an Agent-Based Model." *PLOS ONE*, vol. 16, no. 4, 2021, https://doi.org/10.1371/journal.pone.0249821.

Yoon, Jiho, et al. "Procurement Decisions and Information Sharing under Multi-Tier Disruption Risk in a Supply Chain." *International Journal of Production Research*, vol. 58, no. 5, 2019, pp. 1362–1383., https://doi.org/10.1080/00207543.2019.1634296.

Zhang, Allan N., et al. "Quantifying Supply Chain Disruption: A Recovery Time Equivalent Value at Risk Approach." *International Journal of Logistics Research and Applications*, 2021, pp. 1–21., https://doi.org/10.1080/13675567.2021.1990872.

Zhou, Shuli, et al. "Optimizing Spatial Allocation of COVID-19 Vaccine by Agent-Based Spatiotemporal Simulations." GeoHealth, vol. 5, no. 6, 2021, https://doi.org/10.1029/2021gh000427.

APPENDIX A: NETLOGO CODE FOR SUPPLY CHAIN SIMULATION

```
breed[companies company]


globals
[
  supply_capacity ; set at initialization as: demand per day (slider) * cycle (slider), divided among three suppliers. Capacity is then
                  ; adjusted upward by over_capacity (slider) percentage, and rounded up to nearest whole number.
  goal_inventory ; how much suppliers want to have on hand: ceiling (demand per day * (cycle + SS_days) / 3)
  all_suppliers ; tutrle set of the three suppliers.
]


companies-own
[
  money
  product
  ordered_product
  costs
  price_to_sell
  delivery_time
  daily_profit_list
  profit_list
  ordered_product_list
  order_delay_list
  total_demand
  total_demand_fulfilled
  total_demand_output
```

```
  total_demand_fulfilled_output
]

to setup
  clear-all
  reset-ticks
  tick
  set timed_run? FALSE
  set supply_capacity floor (demand_per_day * over_capacity / 3) ; supply capacity per supplier
  set goal_inventory ceiling (demand_per_day * (cycle + SS_days) / 3) ; supply on-hand goal per supplier
  create-companies 7
  ask companies
  [
    set size 3
    setxy random 20 random 20
    set money 100
    set product 240
    set ordered_product 0
    set total_demand 0
    set total_demand_fulfilled 0
    set profit_list [ ]
    set ordered_product_list [ ]
    set order_delay_list [ ]
    set daily_profit_list [ ]
  ]
  setup-companies
end
```

```
to step
 check-delays
 ask company 6 ;customer buying from retailer
 [
  let temp_demand demand_per_day
  let temp_seller one-of out-link-neighbors
  let temp_product_available [product] of temp_seller
  let counter 0
  while [temp_demand > 0 and temp_product_available > 0]
  [
   buy-and-sell self temp_seller
   set temp_demand (temp_demand - 1)
   set temp_product_available (temp_product_available - 1)
   set counter counter + 1
  ]
  let temp_buyer self
  ask temp_seller
  [
   set daily_profit_list fput (counter * price_to_sell * profit_margin) daily_profit_list
   show daily_profit_list
  ]
  set total_demand_fulfilled total_demand_fulfilled + counter ; this will increment for the whole cycle,
then be set back to 0
 ]
 if ticks mod cycle = 0
 [
  ask company 5 ; sum the daily profit for goods sold by retailer into once-a-week profit
  [
   ifelse length profit_list < cycle
```

```
    [
     set profit_list fput (sum daily_profit_list) profit_list
     show profit_list
     set daily_profit_list [ ]
    ]
    [
     set profit_list fput (sum daily_profit_list) profit_list
     set profit_list but-last profit_list
     show profit_list
     set daily_profit_list [ ]
    ]
   ]
   ask company 5 ; retailer buying from distributor
   [
    let temp_demand (demand_per_day * (cycle + SS_days)) - product ; demand = how much will sell in
a cycle, plus SS, minus inventory
    set total_demand temp_demand ; for the output
    ifelse temp_demand > 0
    [
     let temp_seller one-of out-link-neighbors
     let temp_product_available [product] of temp_seller
     ;let temp_price price_to_sell of temp_seller
     let counter 0
     while [temp_demand > 0 and temp_product_available > 0]
     [
      buy-and-sell self temp_seller
      set temp_demand (temp_demand - 1)
      set temp_product_available (temp_product_available - 1)
      set counter counter + 1
```

```
      ]
      let temp_delay 3 ; later this might be a slider, but for now everyone is a delay of 3 except people
(no delay) and supplier 0
      ask temp_seller ; add this week's profit for the distributor
      [
       ;set temp_delay to seller's delay slider
       ifelse length profit_list < cycle
       [
        set profit_list fput (counter * price_to_sell * profit_margin) profit_list
        show profit_list
       ]
       [
        set profit_list fput (counter * price_to_sell * profit_margin) profit_list
        set profit_list but-last profit_list
        show profit_list
       ]
      ]
      set ordered_product_list fput counter ordered_product_list
      set order_delay_list fput temp_delay order_delay_list
      set total_demand_fulfilled counter
     ]
     [
      set total_demand_fulfilled 0
      let temp_seller one-of out-link-neighbors
      ask temp_seller
      [
       ifelse length profit_list < cycle
       [
        set profit_list fput 0 profit_list
```

```
          show profit_list
         ]
         [
          set profit_list fput 0 profit_list
          set profit_list but-last profit_list
          show profit_list
         ]
        ]
       ]
      ]
      ask company 4 ; distributor buying from manufacturer
      [
       let temp_demand (demand_per_day * (cycle + SS_days)) - product ; demand = how much will sell in
a cycle, plus SS, minus inventory
       set total_demand temp_demand ; for the output
       ifelse temp_demand > 0
       [
        let temp_seller one-of out-link-neighbors
        let temp_product_available [product] of temp_seller
        ;let temp_price price_to_sell of temp_seller
        let counter 0
        while [temp_demand > 0 and temp_product_available > 0]
        [
         buy-and-sell self temp_seller
         set temp_demand (temp_demand - 1)
         set temp_product_available (temp_product_available - 1)
         set counter counter + 1
        ]
```

```
    let temp_delay 3 ; later this might be a slider, but for now everyone is a delay of 3 except people (no delay) and supplier 0
    ask temp_seller
    [
     ifelse length profit_list < cycle
     [
      set profit_list fput (counter * price_to_sell * profit_margin) profit_list
      show profit_list
     ]
     [
      set profit_list fput (counter * price_to_sell * profit_margin) profit_list
      set profit_list but-last profit_list
      show profit_list
     ]
    ]
    set ordered_product_list fput counter ordered_product_list
    set order_delay_list fput temp_delay order_delay_list
    set total_demand_fulfilled counter
   ]
   [
    set total_demand_fulfilled 0
    let temp_seller one-of out-link-neighbors
    ask temp_seller
    [
     ifelse length profit_list < cycle
     [
      set profit_list fput 0 profit_list
      show profit_list
     ]
```

```
        [
          set profit_list fput 0 profit_list
          set profit_list but-last profit_list
          show profit_list
        ]
      ]
    ]
  ]
  ask company 3 ; manufacturer buying from three suppliers
  [
    let temp_demand (demand_per_day * (cycle + SS_days)) - product ; demand = how much will sell in
a cycle, plus SS, minus inventory
    set total_demand temp_demand ; for the output
    if temp_demand > 0
    [
      let temp_counter_0 0
      let temp_counter_1 0
      let temp_counter_2 0
      let temp_product_0 [product] of company 0
      let temp_product_1 [product] of company 1
      let temp_product_2 [product] of company 2
      while [temp_product_0 + temp_product_1 + temp_product_2 > 0 and temp_demand > 0]
      [
        if (temp_product_0 > 0 and temp_demand > 0)
        [
          buy-and-sell self company 0
          set temp_product_0 (temp_product_0 - 1)
          set temp_demand (temp_demand - 1)
          set temp_counter_0 (temp_counter_0 + 1)
```

```
      ]
      if (temp_product_1 > 0 and temp_demand > 0)
      [
        buy-and-sell self company 1
        set temp_product_1 (temp_product_1 - 1)
        set temp_demand (temp_demand - 1)
        set temp_counter_1 (temp_counter_1 + 1)
      ]
      if (temp_product_2 > 0 and temp_demand > 0)
      [
        buy-and-sell self company 2
        set temp_product_2 (temp_product_2 - 1)
        set temp_demand (temp_demand - 1)
        set temp_counter_2 (temp_counter_2 + 1)
      ]
    ]
    set ordered_product_list fput temp_counter_0 ordered_product_list
    set order_delay_list fput supplier_0_delay order_delay_list
    set ordered_product_list fput temp_counter_1 ordered_product_list
    set order_delay_list fput supplier_1_delay order_delay_list
    set ordered_product_list fput temp_counter_2 ordered_product_list
    set order_delay_list fput supplier_2_delay order_delay_list
    set total_demand_fulfilled (temp_counter_0 + temp_counter_1 + temp_counter_2)

    set-profit company 0 temp_counter_0
    set-profit company 1 temp_counter_1
    set-profit company 2 temp_counter_2
  ]
]
```

```
  do-plots
  ask companies
  [
   set total_demand_output total_demand
   set total_demand 0
   set total_demand_fulfilled_output total_demand_fulfilled
   set total_demand_fulfilled 0
  ]
 ]
  ifelse Disrupt_0
  [ set-inventory company 0 0 ]
  [ set-inventory company 0 supply_capacity ]
  ifelse Disrupt_1
  [ set-inventory company 1 0 ]
  [ set-inventory company 1 supply_capacity ]
  ifelse Disrupt_2
  [ set-inventory company 2 0 ]
  [ set-inventory company 2 supply_capacity ]

 tick
 run-scenarios
 if ticks >= model_duration and timed_run?
 [ stop ]
end

to run-scenarios
 (ifelse
 breaks = 0
```

```
[ if ticks = 251 [ set timed_run? TRUE ] ]
breaks = 42
[
 if ticks = 70
 [
  (ifelse scenario = "0"
   [ set Disrupt_0 TRUE ]
   scenario = "01"
   [ set Disrupt_0 TRUE set Disrupt_1 TRUE ]
   scenario = "12"
   [ set Disrupt_1 TRUE set Disrupt_2 TRUE ]
   scenario = "012"
   [ set Disrupt_0 TRUE set Disrupt_1 TRUE set Disrupt_2 TRUE ])
 ]
 if ticks = 112
 [
  (ifelse scenario = "0"
   [ set Disrupt_0 FALSE ]
   scenario = "01"
   [ set Disrupt_0 FALSE set Disrupt_1 FALSE ]
   scenario = "12"
   [ set Disrupt_1 FALSE set Disrupt_2 FALSE ]
   scenario = "012"
   [ set Disrupt_0 FALSE set Disrupt_1 FALSE set Disrupt_2 FALSE ])
 ]
 if ticks = 251 [ set timed_run? TRUE ]
]
breaks = 70
[
```

```
 if ticks = 70
 [
  (ifelse scenario = "0"
   [ set Disrupt_0 TRUE ]
   scenario = "01"
   [ set Disrupt_0 TRUE set Disrupt_1 TRUE ]
   scenario = "12"
   [ set Disrupt_1 TRUE set Disrupt_2 TRUE ]
   scenario = "012"
   [ set Disrupt_0 TRUE set Disrupt_1 TRUE set Disrupt_2 TRUE ])
 ]
 if ticks = 140
 [
  (ifelse scenario = "0"
   [ set Disrupt_0 FALSE ]
   scenario = "01"
   [ set Disrupt_0 FALSE set Disrupt_1 FALSE ]
   scenario = "12"
   [ set Disrupt_1 FALSE set Disrupt_2 FALSE ]
   scenario = "012"
   [ set Disrupt_0 FALSE set Disrupt_1 FALSE set Disrupt_2 FALSE ])
 ]
 if ticks = 251 [ set timed_run? TRUE ]
]
breaks = 98
[
 if ticks = 70
 [
  (ifelse scenario = "0"
```

```
    [ set Disrupt_0 TRUE ]
    scenario = "01"
    [ set Disrupt_0 TRUE set Disrupt_1 TRUE ]
    scenario = "12"
    [ set Disrupt_1 TRUE set Disrupt_2 TRUE ]
    scenario = "012"
    [ set Disrupt_0 TRUE set Disrupt_1 TRUE set Disrupt_2 TRUE ])
  ]
  if ticks = 168
  [
   (ifelse scenario = "0"
    [ set Disrupt_0 FALSE ]
    scenario = "01"
    [ set Disrupt_0 FALSE set Disrupt_1 FALSE ]
    scenario = "12"
    [ set Disrupt_1 FALSE set Disrupt_2 FALSE ]
    scenario = "012"
    [ set Disrupt_0 FALSE set Disrupt_1 FALSE set Disrupt_2 FALSE ])
  ]
  if ticks = 251 [ set timed_run? TRUE ]
 ])
end

to buy-and-sell [buyer seller]
 ask seller
 [
  set money (money + price_to_sell)
  set product (product - 1)
  ask buyer
```

```
    [
      set money (money - price_to_sell)
      ;set ordered_product (ordered_product + 1)
    ]
  ]
end

to set-profit [supplier amount_sold]
  ask supplier
  [
    ifelse length profit_list < cycle
    [
      set profit_list fput precision (amount_sold * price_to_sell * profit_margin) 1 profit_list
      show profit_list
    ]
    [
      set profit_list fput precision (amount_sold * price_to_sell * profit_margin) 1 profit_list
      set profit_list but-last profit_list
      show profit_list
    ]
  ]
end

to set-inventory [supplier capacity]
  ask supplier
  [
    ifelse (goal_inventory - product <= capacity)
    [ set product goal_inventory ]
    [ set product (product + capacity) ]
```

```
  ]
end

to check-delays
  ask companies
  [
;   if (not empty? order_delay_list)
;   [
;     show (word "delay list: " order_delay_list)
;     show (word "product: " product)
;   ]
    let temp_length length order_delay_list
    while [temp_length > 0]
    [
      set order_delay_list (replace-item (temp_length - 1) order_delay_list (item (temp_length - 1)
order_delay_list - 1))
      set temp_length (temp_length - 1)
    ]
;   if (not empty? order_delay_list)
;   [
;     show (word "delay list: " order_delay_list)
;   ]
    while [member? 0 order_delay_list]
    [
      let temp_position position 0 order_delay_list
      let temp_amount (item temp_position ordered_product_list)
      set product (product + temp_amount)
      set order_delay_list (remove-item temp_position order_delay_list)
      set ordered_product_list (remove-item temp_position ordered_product_list)
```

```
    ]
;    show (word "product: " product)
  ]
end

to do-plots
  if not empty? [profit_list] of company 5
  [
    set-current-plot "Retail weekly profit"
    set-current-plot-pen "pen-0"
    ask company 5
    [ plot item 0 profit_list ]
    if ticks > round (plot_length * cycle)
    [ set-plot-x-range (round (ticks / cycle) - plot_length) round (ticks / cycle) ]
    set-current-plot "Distributor weekly profit"
    set-current-plot-pen "pen-0"
    ask company 4
    [ plot item 0 profit_list ]
    if ticks > round (plot_length * cycle)
    [ set-plot-x-range (round (ticks / cycle) - plot_length) round (ticks / cycle) ]
    set-current-plot "Manufacturer weekly profit"
    set-current-plot-pen "pen-0"
    ask company 3
    [ plot item 0 profit_list ]
    if ticks > round (plot_length * cycle)
    [ set-plot-x-range (round (ticks / cycle) - plot_length) round (ticks / cycle) ]

  ]
end
```

```
to setup-companies
 ask companies
 [
  if who < 3
  [
   set label word "supplier_" who
   set shape "truck"
   set color red
  ]
  ;show label
 ]
 ask company 0
 [
  setxy 4 20
  set product 94
  set price_to_sell supplier_0_price
 ]
 ask company 1
 [
  setxy 4 15
  set product 93
  set price_to_sell supplier_1_price
 ]
 ask company 2
 [
  setxy 4 10
  set product 93
  set price_to_sell supplier_2_price
```

```
]
ask company 3
[
 set shape "house"
 set color turquoise
 setxy 10 15
 set label "manufacturer"
 set price_to_sell 10
]
ask company 4
[
 set shape "pentagon"
 set color yellow
 setxy 16 15
 set label "distributor"
 set price_to_sell 20
]
ask company 5
[
 set shape "square"
 set color blue
 setxy 22 15
 set label "retailer"
 set price_to_sell 40
]
ask company 6
[
 set shape "person"
 set color green
```

```
  setxy 28 15
  set label "customer"
 ]
 ask companies
 [
  (ifelse
  who < 3   ;first choice
  [ create-link-from company 3 ]
  who = 3   ;second choice
  [  ]      ;do nothing in this case
  [ create-link-to company (who - 1) ])  ;else condition
 ]
 set all_suppliers (turtle-set company 0 company 1 company 2)
end
```