# Impact of Inventory Management Policies on Supply Chain Resilience at RiRiShun Logistics

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Abstract: Using one year's transaction level data from a large logistics service provider, this paper employs discrete event simulation to assess various inventory policies for managing supply chain risks and developing resilience. Datasets from a large Chinese Business-To-Consumer firm (RiRiShun Logistics) specialising in the order fulfilment of household appliances were provided. Using the datasets, a discrete event simulation model of RiRiShun's distribution supply chain in two customer regions was developed using anyLogistix™ simulation software. A series of experiments were carried out to analyse the impact of inventory management policies on the performance of its supply chain in the face of disruptions. Results showed that decentralised inventory performed better when dealing with disruptions, while centralised inventory performed better when dealing with demand uncertainty.

## LIST OF ABBREVIATIONS

Table 1: List of abbreviations.

| | |
|---|---|
| ALX | anyLogistix™ |
| B2B | Business To Business |
| B2C | Business To Consumer |
| CDC | Central Distribution Centre |
| CSV | Comma-Separated Values |
| DC | Distribution Centre |
| DES | Discrete Event Simulation |
| LMH | Last Mile Hub |
| LTC | Local Transfer Centre |
| RDC | Regional Distribution Centre |
| SKU | Stock Keeping Unit |
| TTR | Time to Recover |
| TTS | Time To Survive |

## 1 INTRODUCTION

Modern supply chains are highly complex, with those firms engaged in the supply and distribution of business to consumer (B2C) products tending to have multi-echelon networks, often with centrally located, larger warehouses outside urban districts and then smaller order fulfilment facilities located closer to clusters of customers. Such multi-echelon distribution networks present supply chain design and management challenges, where inventory location, product availability and speed of order fulfilment to end customers are key issues. Firms must manage the trade-off between holding inventory at large upstream warehouses, the transportation cost and order cycle time to end customers. In the wake of the COVID-19 pandemic, there is additional focus on designing resilient supply chains, with one approach being to hold increased safety stock, but which comes with increased inventory costs.

This paper employs simulation modelling and uses transaction level data from a large B2C firm (RiRiShun Logistics) to analyse the resilience of its downstream distribution network, with particular focus on the role of inventory management policies. The analysis focuses on where best to store inventory to lower network costs while maintaining service levels to customers when the network is subject to disruptions and increasing levels of demand variation. Previous research (e.g. Berman et al., 2011) shows that storing inventory at higher echelons mitigates

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against downstream disruptions such as stochastic demand, while storing inventory at lower echelons better protects against supply uncertainty.

The remainder of this paper is structured as follows. Section 2 summarises the findings from the relevant literature. A description and preliminary analysis of the datasets provided by RiRiShun Logistics is provided in Section 3. Section 4 describes the development of the simulation model and the experiments that are carried out. Results from the experiments and a discussion are in Section 5. Conclusions, limitations and future work are outlined in Section 6.

# 2 LITERATURE REVIEW

This section provides a summary of the relevant literature related to inventory management policies, with particular focus on supply chain risk, as well as the analytical approach employed in the paper (Discrete Event Simulation).

## 2.1 Inventory Management & Supply Chain Risk

Previous research focusing on the minimisation of inventory costs includes Üster et al. (2008), which identifies four dominant pillars of inventory costs: stock-out, holding, transportation and opportunity costs. While Üster et al. (2008) focus on minimizing system-wide transportation costs, the research described in our paper focuses on the role of inventory allocation policies within a pre-existing distribution network to enhance resilience. Initial allocation of inventory is crucial and several methods for initial allocation are discussed in Liu (2016) and Catalán et al. (2012). Liu (2016) utilises the same data set as our paper and explores the impact inventory allocation has on transhipment and replenishment policies. The distance between distribution centres was identified as a crucial factor in the success of inventory policies and in lowering overall logistics costs. Catalán et al. (2012) explore how best to categorise Stock Keeping Units (SKU) so those often sold together are located at similar locations. The allocation of SKUs in different echelons is also discussed in Nozick & Turnquist (2001), Mao et al. (2019) and Li et al. (2021). The first two of these explain that less popular SKUs should be stored at a higher echelon. There, they will accumulate lower holding costs. This negates the additional cost they incur when they are ordered. These papers also emphasise the need to study the lower echelons of supply chain networks as their inventories are more critical to the network's profitability. Li et al. (2021) focus on the most popular SKU from the most popular client, an approach which significantly decreases the complexity of the real-world problem.

Risk-pooling is a common inventory management tactic in the context of supply chain risk management. Risk pooling means concentrating stock in centralised locations, while risk diversification in this context means spreading inventory across multiple distribution centres (DCs) to lower the impact of disruptions.

Supply chain resilience refers to *"the ability of a system to bounce back from a setback"* (Schmitt & Singh, 2012). The necessity for a closer examination of supply chain resilience has intensified since the COVID-19 pandemic (Ivanov & Dolgui, 2022). Firms no longer see disruptions as exceptional events but rather as part of ongoing business planning, leading to increased focus on designing resilient supply chains.

Schmitt & Singh (2012) discuss the outcomes of holding inventory higher or lower in the supply chain. If a disruption occurs and the majority of inventory is held upstream, the downstream DC's inventory will deplete and will not be easily replenishable. Alternatively, if a disruption occurs when inventory is held further downstream, upstream production output will have to be reduced unless alternative storage facilities are available. Schmitt et al. (2015) investigate the applicability of risk pooling and risk diversification depending on the stochasticity of both demand and supply. It is generally accepted that under deterministic supply and stochastic demand, a centralised inventory is preferred as the demand variance of each demand can be pooled together, lowering operational costs. Conversely, if supply is stochastic and demand is deterministic, a less centralised approach is favourable as disruptions will impact the entire system less. Berman et al. (2011) found that holding inventory centrally was beneficial when stochasticity was introduced to a supply chain. This research found that low variations in demand favoured the centralised method by allowing it to maintain adequate service levels at higher levels of variation. At 50% variation, however, the benefits of risk pooling ceased as the system entered a *" complete shutdown"* regime. Tomlin (2006) and Park et al. (2010) also discuss the effects of risk pooling and risk diversification in the face of disruption, with Tomlin (2006) arguing that risk diversification lowers transport costs and also stating *"Firms that passively accept the risk of disruptions leave themselves open* *to the danger of severe financial and market-share loss".*

### 2.2 Discrete Event Simulation

Discrete Event Simulation (DES) is a method of modelling the operations of a system in which each action or event that takes place changes the state of the system and occurs at a particular time. These times and changes are recorded within the simulation (Law et al., 2007). DES has several advantages as an analytical modelling approach. It enables the creation of a complex network of interrelated operations and the performance of various 'what-if' experiments (Jahangirian et al., 2010). In recent years, it has been used increasingly in supply chain management. For instance, Haque et al. (2022) utilise DES to lower logistics costs, Papakostas et al. (2019) to design dynamic manufacturing networks, Liu et al. (2016) to optimise inventory allocation and transhipment policies and Chu et al. (2015) to sustain adequate fulfilment rates. Furthermore, while mathematical programming and optimisation techniques (e.g. Linear Programming) produce a single point result, DES provides the decision maker with a range of results, often in the form of a distribution and confidence interval. DES also allows for stochasticity. The user can introduce agents (products) into the system at a specified time or a rate with a specified distribution. This control allows the user to see the impact of an increased demand variance and add a certain level of randomness, capturing the true nature of unpredictable real-world problems.

DES has also seen increased adoption and application recently to model supply chain risk and resilience. A range of studies demonstrating the usefulness of applying this technique to disruptions have been carried out (Ivanov, 2017; Ivanov & Rozhkov, 2020; Ivanov & Dolgui 2022). These studies all demonstrate how simulation allows the user to experiment with different transportation and stocking policies in the face of disruptions to examine their impacts on lead times, financial outcomes and network efficiency.

## 3 PRELIMINARY ANALYSIS

This section will provide an introduction to RiRiShun Logistics (RRS) and its operations. In addition, it will describe the transaction level data sets that were used in this research.

### 3.1 Research Context: RiRiShun Logistics

RiRiShun (RRS) Logistics is a Haier Group subsidiary and a leading logistics service provider focusing on home appliance delivery and installation in China. RRS has created a distribution network that can deal with bulkier household appliances (e.g. cookers, refrigerators, washing machines etc.) which require special handling and installation. In 2021, RRS supported the Institute for Operations Research and Management Science (INFORMS) Manufacturing & Service Operations Management (MSOM) Society's "Data-Driven Research Challenge" by providing MSOM members with a single year's actual logistics operational-level data. The data include over 14 million orders from 149 consigners with deliveries to an estimated 4.2 million customers in China and handles 18,000 SKUs.

The RRS distribution network is designed in a hierarchical manner. At the top are seven national central distribution centres (CDCs). Below are 26 regional distribution centres (RDCs); at the lowest level there are 100 local transfer centres (LTCs). These are serviced by more than 6,000 last-mile hubs (LMHs), which deliver directly to the end customers. A high level outline of the network is illustrated in Figure 1.

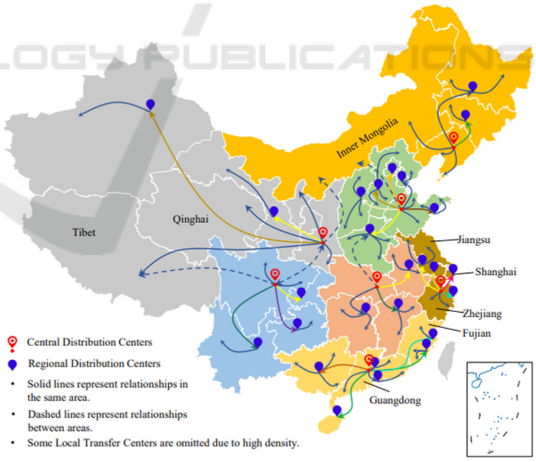


Figure 1: RiRiShun Distribution Network (Guo et al., 2021).

Typically, the logistics for each Chinese province in RRS' service area are provided by one CDC or RDC. However, due to the uneven population distribution, some provinces have more than one RDC, while others might not have any and be served by a neighbouring province. RRS provides both Business to Customer (B2C) and Business to

Business (B2B) operations, but for the focus of the research challenge, the focus is only on its B2C supply chain.

## 3.2 Data Description

RRS data consist of seven CSV files, each containing information on a particular logistics segment. The tables in each file describe details on individual orders, the products being delivered, appointments made by customers, granular delivery details, and the customers themselves. The data sets are linked by a standard primary key (*order_no*). The purpose of the key is to provide a way to join the data from different tables or data sets into a single table or data set. The key matches up rows in different data sets with the same value so that the corresponding data can be combined into a single row. Each table also has a foreign key to distinguish between each row of their respective tables. Table 2 depicts the *Delivery_details* data set with examples of each value.

Sometimes when a SKU is ordered, it must be transhipped through each echelon of the distribution network and even go through a LMH before being delivered to a customer. Each sub-process is detailed in the *Delivery_details* table. Of course, the order to which each sub-process is a part of is detailed in the *order_no* column, and the unique identifier for each row in the table is given in the *rrs_pool_node_info_id* column. When an order is placed, a DC is assigned to track and ensure that the order is delivered. That DC is specified through *operation_center_code*. As the SKU moves closer to the customer, the warehouse that it departs is shown in *orig_code* and that it enters is *dest_code*. To clarify, the locations possible in the *orig_code* column are origin centres, transfer centres, destination centres and LMHs. The values possible in the *dest_code* column are transfer centres, destination centres, LMHs and the GB codes for specific Chinese districts (Postcodes). The type of operation between the two locations is detailed in the *node_code* column. The example given in Guo et al. (2021) is "QS", meaning "signed". This means that the *orig_code* and *dest_code* is the name of an LMH and the customer's location, respectively.

The *Appointment_details* and *SKU_details* tables describe how long each order took to be delivered and product-specific information, respectively. These tables were merged through the *order_no* column to create a table that described all transactions between warehouses pertaining to the most frequently sold SKU with the mean lead time of those orders. In this way, our paper follows the methodology proposed by Li et al. (2021) that focuses solely on the most popular RRS SKU to reduce processing times.

## 3.3 Data Cleaning

To create an accurate simulation model of the RRS network, the locations of all DCs were required. However, RRS did not provide this information. Instead, they provided a supplementary *Distance_information* table, which contains a matrix detailing the distances between all 103 warehouses. Guo et al. (2021) also provided a blank map of China depicting the locations of the CDCs and RDCs. The locations of the LTCs were found through triangulation. To find one LTC, circles were drawn digitally around three known locations. The radii of each circle were given as the distance between the three known locations and the LTC's location. Where these three circles intersected was determined to be the approximate location of the LTC. Figure 2 illustrates the locations of all RRS DCs and LTCs. The CDC icons are navy, the RDC icons are blue and the LTC icons are green.

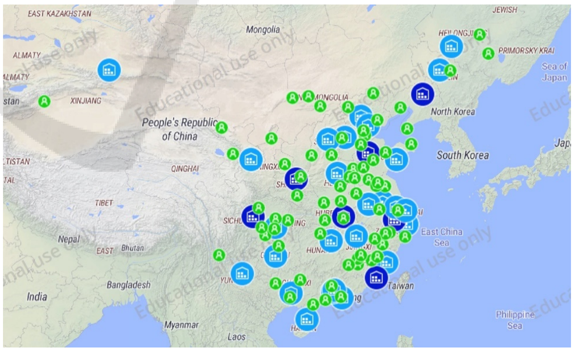


Figure 2: Location of RRS distribution centres.

Table 2: Description of the Delivery_details table.

| Field | Data Type | Sample Value |
|---|---|---|
| rrs_pool_node_info_id | bigint | 01a967a7bda6a071e7b4f71275e102aa |
| order_no | varchar | 0d0a09d33b1190313a392d619e9d223a |
| operation_center_code | varchar | RRSZX076 |
| orig_code | varchar | rrs_wd_3927 |
| dest_code | varchar | GB00264 |
| node_code | varchar | QS |
| node_operation_date | datetime | 2019-06-04 23:59:59 |

### 3.4 Data Construction

To create a model that accurately represents the RRS network, the number of times each DC sent a product to and received a product from another DC had to be known. Since RRS only provided the locations of DCs and not LMHs, this paper will only focus on interactions between the top three echelons of the network. Consequently, the model will treat all LTCs as customers, whereas CDCs and RDCs will be treated as DCs. To generate the number of times each DC sent and received a product from another DC, the *Delivery_details* data set required cleaning. All rows where the sender and the receiver of the product were not named had DCs deleted. Moreover, the *Delivery_details* documented processes that did not involve two DCs, but rather a process that started and finished within the same DC. Rows, where the sender and the receiver were the same, were also deleted.

Table 3 depicts the top five rows of the data frame created (using Python) during the data construction phase. The data represents only the most frequently sold SKU (*1936c558*) in the busiest quarter of the year (June to August). Each combination of sender and receiver was created and counted. This data frame also showed that, within the top three echelons of the network, LTCs rarely sent SKUs, while CDCs and RDCs seldom received SKUs. This demonstrates that modelling the first two echelons of the network as DCs and the LTC echelon as customers is appropriate.

Table 3: Top five rows of the "combinations count" data frame.

| Index | Sender - Receiver | Count |
|---|---|---|
| 0 | RRSZX081 - RRSZX083 | 5,867 |
| 1 | RRSZX033 - RRSZX021 | 4,949 |
| 2 | RRSZX083 - RRSZX086 | 4,059 |
| 3 | RRSZX043 - RRSZX048 | 3,802 |
| 4 | RRSZX074 - RRSZX079 | 3,429 |

## 4 SIMULATION MODELLING

In this section, an outline of the simulation modelling approach will be provided. Based on this, an experimental test design will be generated, so that different questions in relation to the impact of inventory management policies on supply chain resilience can be answered. Section 2 previously discussed the appropriateness of DES to analyse supply chains (e.g. Chu et al., 2015; Liu et al., 2016; Papakostas et al., 2019; Haque et al., 2022 all used this modelling approach to generate results for their respective research). As previously mentioned, DES has advantages over other approaches: its ability to consider stochasticity, disruptions and real-time monitoring of a supply network. Li et al. (2021) asserts that DES allows an entire network to be considered and optimised rather than one specific aspect. The modelling software used by Li et al. (2021) was AnyLogic. In 2014, AnyLogic created a spin-off product to deal specifically with simulation modelling of supply chains called anyLogistix™ (ALX). ALX allows users to create a digital twin of supply chains of any size to design and optimise network features and strategies. ALX has been previously used to model disruptions and to analyse what-if scenarios (Ivanov, 2017; Ivanov & Rozhkov, 2020; Ivanov & Dolgui 2022).

### 4.1 Simulation Model Development

ALX enables the creation of a simulation model to simulate and test supply chain scenarios for RRS to evaluate its supply chain performance, with particular focus on inventory management policies and their impact on supply chain resilience. The model is designed to focus on metrics such as service levels, lead times, inventory costs and transport distances.

The model's features include the DCs/factories, customers, locations, demand data, suppliers and vehicles. The locations of each DC and customer are based on real DCs in the RRS network and are connected automatically in the ALX model using accurate road network data. The demand for each customer was found by analysing the RRS data for the busiest quarter of the year and a demand coefficient was applied to each month based on the number of transactions done per month. The lead time for product *1936c558* was found to be 42 hours, which was chosen as the expected delivery time, and orders were dropped if delivery was not possible within this period.

### 4.2 Experimental Design

ALX functionality provides a range of experiments to run. The most basic, "Simulation Experiment", simply simulates the model that the user creates. However, other experiments exist that focus on safety stock and risk analysis. Ivanov (2017) used the basic "Simulation Experiment" to assess the performance of different inventory policies. When running one of these experiments, the user can specify a start and end date, create dashboards to show the simulation results and when imposing demand stochasticity, specify how many iterations of the experiment to run. The user can then adjust the model, rerun the simulation and compare the results. The experiments described in our paper were focused on two of RRS's customer regions in China: Foshan and Chengdu.

This research aims to answer two primary questions regarding the impact of inventory management policies on supply chain resilience. The first question is whether RRS supply chain network performs better if most of its stock is centrally held at a higher echelon of the supply chain or if the stock is held in decentralised locations at a lower level of the supply chain network. While prior literature discussed appropriate safety stock levels and inventory policies to deal with disruptions (e.g. Schmitt et al., 2015), it appears none to date have investigated whether keeping stock upstream or downstream makes supply chains more resilient. Two important metrics of supply chain resilience are Time To Survive (TTS) and Time To Recover (TTR) (Simchi-Levi et al., 2014; Nguyen, 2021). TTS is the length of time a supply chain can maintain adequate service levels after a disruption, while TTR is the time it takes a supply chain to achieve normal service levels after the drop caused by the disruption.

The second research question is how stochastic demand affects the performance of RRS supply chain network. Prior research has shown that holding inventory centrally can better cope with the stochasticity of demand when supply is deterministic, due to the risk-pooling effect where the variance of all customers is pooled together to create one demand variance rather than several (Schmitt et al., 2015). However, when demand is deterministic and supply is stochastic, a decentralised network where the inventory is more dispersed is better suited. While some authors have explored these findings, there has been little examination of how networks with centralised and decentralised stock cope with demand variance. Although ALX software makes varying demand easy, it is more difficult to add stochasticity to supply. Another previous study found that a central system could perform well at higher levels of demand variation, but at a certain threshold, the benefits of holding inventory centrally become negligible as the system naturally holds no safety stock (Berman et al., 2011).

Assumptions for each model variation are discussed in the following sub-sections. By configuring the model in this way, it is possible to test different scenarios and accurately record the key performance indicators (KPI) of the supply chain.

### 4.2.1 Upstream Versus Downstream

It was decided that the model would have a capacity of 6,000 units. To differentiate between a centralised and decentralised network, these 6,000 units would be separated in different ways. For the centralised network, 60% of the capacity was allocated to the CDC. The remaining 40% were dispersed based on demand. The capacities for each DC in the Upstream model can be seen in Figure 3.

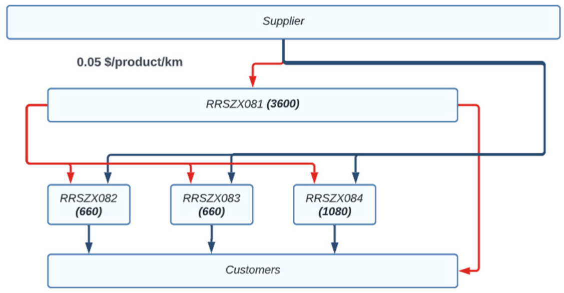


Figure 3: Product flow – upstream model.

The decentralised model more evenly dispersed the 6,000 units. Two DCs were allocated 30% of the 6,000 units while the other two DCs were allocated 20% each (Figure 4).

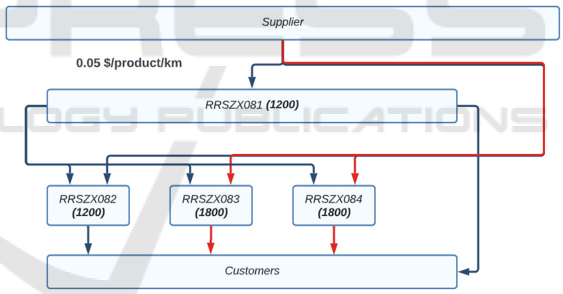


Figure 4: Product flow – downstream model.

Both models only allow the products to move downwards through the distribution network and the LTCs act as customers. The red lines in Figures 3 and 4 indicate the impact of the disruption. The first experiment is examining each model's reaction to a full DC closure where no products can flow into or out of the closed DC. The disruption will last 30 days and, in both cases, will impact 60% of the capacity of the network. Therefore, the CDC in the Upstream model carrying 60% network capacity will close, while two RDCs carrying 30% of the network capacity will close in the Downstream model. An (*r, Q*) was used for the DCs in both scenarios where *r* was one-third of the DC capacity and *Q* was two-thirds of the DC capacity.

#### 4.2.2 Demand Variance

This experiment introduces downstream disruptions in the form of varying the demand of each customer. A sensitivity analysis was performed to do this. In the Upstream and Downstream models with disruptions, the customers were given a demand with a triangular distribution. The former weekly demand was the mode value. In contrast, the minimum and maximum values were changed for each experiment since Berman et al. (2011) found that the benefits of risk pooling became negligible at 50%, the minimum values were chosen to be 80%, 60%, and 40% of the mode value. In contrast, the maximum values were chosen to be 120%, 140%, and 160% of the mode value. This range should indicate how demand variation affects both models while triggering the threshold at which the models enter the "Complete Shutdown" regime.

## 5 RESULTS & DISCUSSION

This section outlines the results obtained through the experimentation process and discusses their findings.

### 5.1 Upstream Versus Downstream

Before comparing how the Upstream and Downstream models coped with 60% capacity disruptions, the two scenarios must be compared performing without any issues. Table 4 contains results from the four simulations that were run for this experiment. The first thing to note is that both models had an almost perfect service level. The Upstream and Downstream models dropped two and one order, respectively, out of a total of the 210 that was expected. In both cases, the service level remained above 90% the entire time.

Schmitt et al. (2015) state that a network structure that holds its inventory downstream in more decentralised locations will be better adapted to handle disruptions. It would appear from the simulation results that is accurate. Upon a 60% capacity disruption, the TTR value for the Upstream model was 175 days compared to 91 days in the Downstream equivalent. This suggests significantly higher resilience. The Total Service Level of each model reinforces this point. The mean service level of the Upstream model fell from 99% to 91%, almost twice as great a decrease as the Downstream model. It can be seen in Figures 5 and 6 that the service level of both models reaches approximately 65% by day 30. However, where the Downstream model recovers after that, the Upstream model continues to fall another 10% by day 45. This indicates that the disruption impacts the Upstream model more aggressively and enforces a longer recovery time.

Schmitt et al. (2015) argued that by *"Not putting all the firms' eggs in one basket"* a supply chain would be less affected by disruptions, *"although the same number of eggs* may be destroyed, they are not all destroyed at once". When the majority of stock is held at one location, the other locations are worse prepared to deal with a sudden increase in demand.

Based on the results from this experiment, it is suggested that inventory should be held downstream in decentralised locations if there is a risk of disruptions. The lesser impact sustained and quicker recovery times suggest that holding stock at RiRiShun's RDC levels increases its supply chain's resilience and maintains higher levels of customer satisfaction.

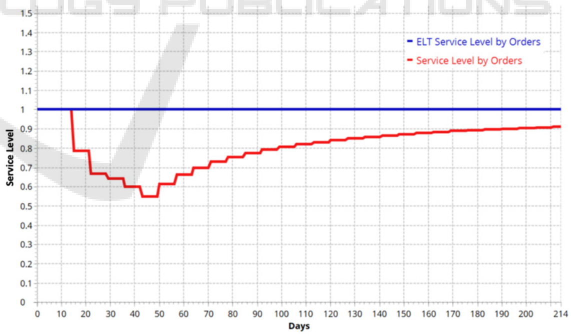


Figure 5: Service level of upstream model with disruptions.

Table 4: Results from upstream and downstream simulations (with & without disruptions).

| Scenario | Upstream | | Downstream | |
|---|---|---|---|---|
| Version | No Disruption | Disruption | No Disruption | Distruption |
| Distance Travelled (km) | 158,583 | 151,499 | 208,805 | 202,229 |
| Dropped Orders | 2 | 19 | 1 | 10 |
| Total Service Level | 0.90 | 0.91 | 0.995 | 0.952 |
| Days Below 90% Service Level | 0 | 175 | 0 | 91 |

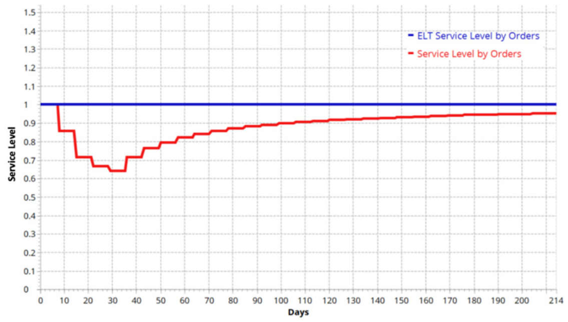


Figure 6: Service level of downstream model with disruptions.

## 5.2 Demand Variance

Berman et al. (2011) and Schmitt et al. (2015) found that holding inventory in a central location rather than several decentralised locations was beneficial when the demand from multiple customers had variation. The reason for this was based on the work done by Chen & Lin (1989) emphasising the benefits of risk pooling. If one DC serves multiple customers with demand stochasticity, all variations can be combined to mitigate risk.

According to the results in Table 5, the effects of demand variation are handled better in the Upstream model. The number of dropped orders decreases as the demand stochasticity increases. This contrasts with the Downstream model where the number of dropped orders increases slightly. Total Service Level is inversely proportional to the number of dropped orders in a network which explains the increasing service level in the Upstream model and the decreasing service level in the Downstream model.

While the Upstream model performs better, neither system appears to be affected significantly by the demand variation as much as expected. The Upstream model appears to perform better as the level of variation increases. Berman et al. (2011) stated that a centralised system could operate at normal levels for more extreme variation. However, that research also suggested a threshold at which the benefits of risk pooling would diminish. That threshold was found to be 50%. However, the results from this experiment show that at 60% variation, the benefits of risk pooling are even more evident.

One explanation for this could be how Berman et al. (2011) define the "Complete Shutdown" regime where holding inventory centrally no longer realises a benefit. In that paper, the model stops holding safety stock due to the variation in demand. As the inventory in each DC is 0, all met demand is that which is back-ordered. Since no back-ordering is allowed in the ALX model, the only demand that can be met is orders with the required stock. The CDC in the Upstream model has a larger reserve of stock throughout the simulation and, therefore, can handle larger orders. As the demand fluctuates, larger orders that high-capacity DCs can meet become more common. Since the Downstream model spreads its inventory more evenly across the four DCs, those larger orders that occur at 60% variation are less likely to be met. This can explain the higher number of days with an inadequate mean service level in the Downstream model.

Building on previous literature, the results of the simulation experiments suggest that supply chains that see large demand fluctuations would be better to hold stock centrally. Holding stock in fewer locations makes infrequent large orders more likely to be met. The benefit of risk pooling was also identified in this experiment. Supply chains that are prone to risks and demand stochasticity require a more detailed examination, as the results from the first two experiments in this thesis promote two different inventory strategies.

# 6 CONCLUSIONS

This section summarises the findings of the simulation experiments based on RiRiShun data for

Table 5: Results from the demand variance experiment.

| Scenario | Upstream | | | | Downstream | | | |
|---|---|---|---|---|---|---|---|---|
| Version | Disruption | +/- 20% | +/- 40% | +/- 60% | Disruption | +/- 20% | +/- 40% | +/- 60% |
| Distance Travelled (km) | 17,080 | 19,186 | 16,575 | 20,838 | 17,993 | 18,152 | 18,244 | 17,994 |
| Dropped Orders | 19 | 17 | 17 | 5 | 10 | 10 | 11 | 12 |
| Total Service Level | 0.91 | 0.919 | 0.919 | 0.976 | 0.952 | 0.952 | 0.948 | 0.943 |

two of its regions in China. In the scenario where disruptions are probable or where risk analysis of its supply chain is in the early phases, decentralised inventory storage is preferred. This option leaves customers with more options from which to receive demand. Disruptions, particularly ones where DCs close entirely, impact supply chains with inventory held Upstream more severely and impose a longer TTR. While decentralised networks are advantageous for disruptions higher in the network hierarchy, centrally held stock takes advantage of risk pooling to mitigate the risks associated with demand variations. This results showed that an increase in the volatility of demand had little effect on the Upstream model while having greater and negative impacts on the Downstream model.

The results from the simulation experiments align with those of Schmitt et al. (2015) in suggesting that supply chains with decentralised inventory are better equipped to deal with disruptions. With more non-disrupted DCs to complete orders, there is a higher order completion rate. However, Upstream models are more adept at coping with demand fluctuations. The results also agree with the work done by Berman et al. (2011), citing risk pooling as the reason for this.

There were differences in the results of the simulation experiments to those described by Berman et al. (2011), who outlined the demand variance threshold at which Upstream supply chains no longer had an advantage over Downstream models. The results from our experiments suggested that Upstream models would become increasingly effective at dealing with demand fluctuations. As the spread of order sizes increases, there will be more orders that large stores of inventory can only fulfil.

There were a number of limitations to the research described in this paper. RRS provided the datasets to the MSOM Data-Driven Research Challenge to facilitate academic researchers to carry out a range of analytical studies. However, no direct contact was provided by either RRS or MSOM to aid researchers in improving these policies or to provide valuable context to some of the data. One aspect of the supply chain that could have used clarification is whether orders could be split between two DCs to meet demand. This was highlighted as beneficial to supply chain performance but was not implemented in the ALX model.

Both the Upstream versus Downstream and Demand Variance experiments focused on how supply chains with centralised and decentralised inventory react to disruption in the form of DC closures and demand fluctuation. However, there was an experiment to investigate the optimal location of stock when both types of disruptions are introduced. A suggestion for further research would be to introduce a variety of disruptions and apply them in specific combinations to see where the inventory should be held in each of those scenarios. Additionally, RRS provides a good framework to experiment with different supply chain structures. While the research described in this paper focused initially on two of RRS regions in China, there are a further five regions with different geographies and structures. It would be interesting to apply disruptions to all seven regions and examine the effects of network geography on supply chain resilience. Further progress in this area might lead to the development of a framework whereby supply chain decision makers can decide what the best national inventory strategies are solely by examining the structure of the supply chain network.

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