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AN AGENT-BASED SIMULATION MODEL TO MITIGATE THE BULLWHIP EFFECT VIA INFORMATION SHARING AND RISK POOLING

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ABSTRACT

The bullwhip effect, a phenomenon of progressively larger distortion of demands across a supply chain, can cause chaos and disorder with amplified supply and demand misalignment. In this research, we investigate ways to decrease the bullwhip effect via risk pooling and information sharing through a simulation study. An agent-based simulation model was developed to evaluate how risk pooling and information sharing between distinct entities in a supply chain can reduce the bullwhip effects. Specifically, we are interested in the effectiveness of these two strategies through their interplay when they are applied simultaneously and separately. We simulate a three-echelon supply chain by considering one manufacturer, one wholesaler, and two retailers. Four scenarios are evaluated by varying the information sharing strategy (centralized and decentralized), and with and without a risk pooling policy. The results show that when both strategies are adopted, the supply chain faces less order amplification throughout the supply chain.

1 INTRODUCTION

The bullwhip effect is very common, and sometimes inevitable, in supply chain management (Dai et al. 2017). It refers to the distortion of information that is realized from the magnification of the order variance as orders move upstream in the supply chain (Dejonckheere et al. 2003; Wang and Disney 2016) and causes a discrepancy between supply and demand that leads to difficulties in supply chain management planning (Li et al. 2016). It also increases operational costs (Cannella et al. 2013), leads to poor customer service (Lee et al. 1997a; Lee et al. 1997b), increases inefficiencies (Metters 1997), and realizes needless safety stock (Jakšič and Rusjan 2008). Therefore, the attenuation of the bullwhip effect is one of the major focuses of supply chain researchers (Thomas et al. 2011). A detailed examination of the research around the causes of the bullwhip effect can be found in the study of Bhattacharya and Bandyopadhyay (2011).

A classic supply chain is illustrated in Figure 1, depicting both the information flow and the material flow. The progressively larger fluctuations of demands propagate from Customer to Retailer, Wholesaler, and finally Manufacturer. One of the most suggested solutions to mitigate the bullwhip effect is information sharing (Chen et al. 2000), as shown in Figure 2. Information sharing enables parties

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throughout the supply chain to better communicate and predict changes. It allows better planning and increases efficiency by smoothing production and lowering inventories (Chatfield 2009). The value of this type of method is proven to be highly beneficial when demand varies. Lee et al. (2000) show that information sharing can dramatically reduce inventory and save money for the manufacturer. Similar research by Wu and Cheng (2008) proves the same in a multi-echelon supply chain. The study conducted by Cachon and Fisher (2000) explores two different levels of information sharing, traditional and full. The research states that traditional information sharing happens if the supplier only monitors the retailer's order. Full information sharing occurs when the supplier can immediately see the retailer's inventory data. The study proves that full information sharing is the most effective type of sharing. A study by Zhou and Benton (2007) shows that supply chain performance can be improved with effective supply chain practices and information sharing. Information sharing is commonly referred to as centralized information.

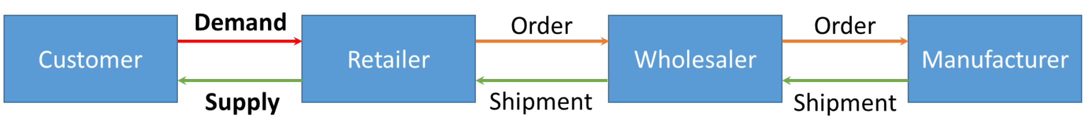

Figure 1: Traditional supply chain.

Another solution to reduce the bullwhip effect is risk pooling, as shown in Figure 3. Risk pooling is a statistical concept that refers to the practice of clustering the risks of a supply chain to make the risk more "certain". This concept uses a centralized inventory policy to plan for inventory. It assumes if the demand at one retailer is higher than the average, it will be lower at other retailers. Instead of keeping the safety stock separately for each retailer/wholesaler, it aggregates the safety stock by considering the demand variance of multiple retailers/wholesalers together (Mak and Shen 2012). Thus, the risk is pooled for the multiple retailers/wholesalers by the upstream stages of a supply chain. The study of Sucky (2009) indicates that the bullwhip effect is overestimated given a simple supply chain and risk pooling effects. Their study explores a three-stage supply chain with two retailers, a wholesaler, and a manufacturer. The study argues that most research around the bullwhip effect fails to include risk pooling effects, and it needs to be considered.

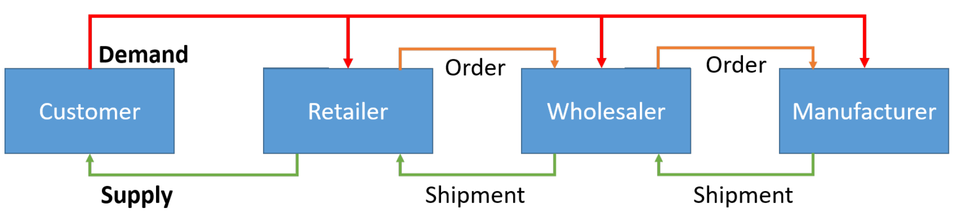

Figure 2: Supply chain with information sharing and no risk pooling.

Traditionally, two approaches are used in studies related to the bullwhip effect: simulation-based and analytical methods (Disney et al. 2004). Analytical or numerical studies produce exact and controlled solutions and assess pertinent factors that affect the system. However, it is challenging to comprehend the effect of each factor and integrate multiple factors on the entire supply chain due to its complexities (Min and Zhou 2002). With the increase in computational power and the availability of such resources, simulation-based models have gained popularity and enable more complex and thorough studies in supply chain management (Kleijnen 2005). Simulation-based studies also enable real-time adaptability and stochasticity tolerance, which is not possible with analytical models. A model created by Chinh et al. (2013) used agent-based simulation to measure the stability of a supply chain using lead time and stochastic demand.

Many studies have been conducted investigating the bullwhip effect but a few of the studies have looked at the impact of both risk pooling and information sharing on the bullwhip effect as seen in Figure 4. Research conducted by Li et al. (2016) study both strategies and evaluate their effects on the container shipping market industry. By using these two methods of reducing the bullwhip effect, their study illustrates how to improve supply chain planning using analytical models. However, their study is limited to two retailers, without the consideration of a more practical and complex distribution network. They did not show the impact of increasing lead time on the effectiveness of those mitigation strategies and only considered constant lead times. On the other hand, agent-based simulation modeling can handle more complex supply chain networks and deal with stochastic lead times easily. Therefore, this study extends the research of Li et al. (2016) by building an agent-based simulation model of a generic supply chain to measure the bullwhip effect while information sharing and risk pooling are applied as a mitigation strategy. We have incorporated the stochastic lead time in our study and presented the impact of increasing lead time on the efficiency of those mitigation strategies.

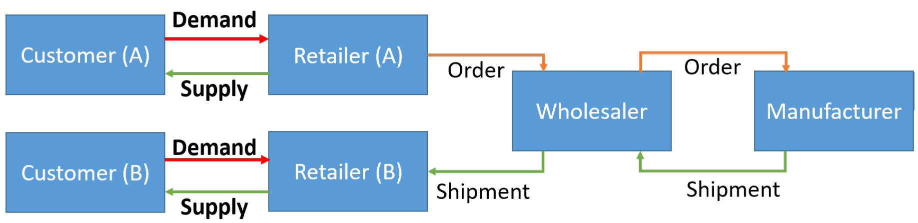

Figure 3: Supply chain with no information sharing and with risk pooling.

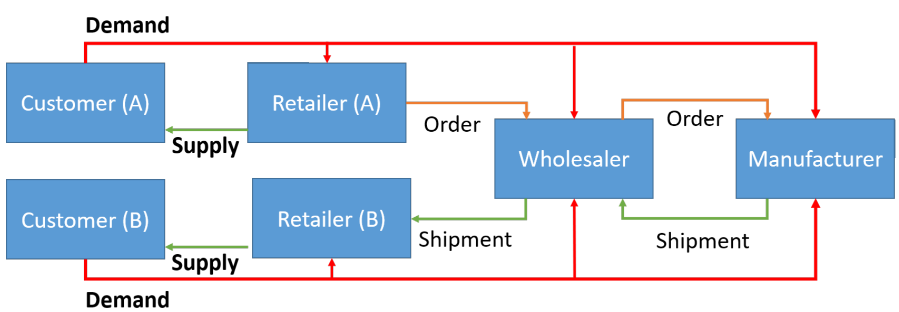

Figure 4: Supply chain with information sharing and with risk pooling.

The organization of this paper is as follows. The following section presents an agent-based simulation approach for this problem, followed by the numerical experiments in AnyLogic software. Finally, the last section discusses our conclusions.

2 AGENT-BASED SIMULATION MODEL TO MEASURE THE BULLWHIP EFFECT IN A SUPPLY CHAIN

Agent-based modeling and simulation is a popular tool nowadays to build models of complex systems such as supply chains (Abar et al. 2017). In this simulation approach, different components of a system are described as agents. Agents interact with each other in an environment. The behavior of an agent is modeled using a set of simple rules. It is easy to identify the impact of different factors on the behavior of agents and on the outcomes of a model. Agent-based techniques enable the system to dynamically self-adapt and strengthen in response to changing environmental circumstances and other disturbances (Abar et al. 2017).

In this paper, we have used an agent-based modeling approach to simulate a traditional supply chain for measuring the bullwhip effect and the impact of risk pooling, and information sharing among the stages of that supply chain in mitigating the bullwhip effect. A three-stage supply chain with two retailers, a wholesaler, and a manufacturer, is considered to build the model. There are four primary agents named *retailer1*, *retailer2*, *wholesaler*, and *factory/manufacturer*, respectively. Demand, order, and shipment are defined as agent types. Each agent can interact with the other via sharing information (order/demand) and delivering products. Customers generate demand at a particular time and the demand information is passed to the retailers, where the retailers fulfill the demand. Other agents receive orders from downstream agents, and they fulfill the order by sending a shipment. Customers are not considered as an agent because they are just creating the demand which is accomplished by using an event in the simulation. All the agents follow a replenishment policy and place orders to their upstream agent. If an agent is placed at the top of the supply chain (*factory/manufacturer*, i.e., there is no upstream agent), it will self-generate orders. The terms 'stage' and 'agent' will be used interchangeably throughout this section.

2.1 Assumptions

While using agent-based simulation to create our model, we make the following assumptions:

- A three-stage supply chain is assumed, which operates 24-hours each day, including two retailers, a wholesaler, and a factory/manufacturer.
- Customer demands are identifiable, identical, and independently distributed among various time periods. Each *retailer* serves separate markets.
- It is assumed that all stages of the supply chain agree to make use of identical order-up-to policies and the same moving average forecasting technique. If the calculated order quantity was negative, then no order is placed to the subsequent stage of the supply chain for that period (similar to Sucky (2009)).
- Each stage accesses the order-up-to level information of the multiple periods at the start of every period and makes a goal for the order quantity for that time period and the order is placed (similar to Li et al. (2016)).
- Each stage fills its customer demands (lower stage's demand/order) with its on-hand inventory. Backlogging is allowed. If this is the case, at the start of a time period, the newly arrived shipment is used to fulfill the backlogged demand first. Ordering and production lead times can be different at various stages.
- Lastly, when information is shared, it is assumed that all the information becomes immediately accessible from every stage of the supply chain.

2.2 Notations

Following notations are used for this paper:

$D_{t,k}$	demand/order quantity for stage k in time period t
z	desired service level
N	number of time periods for forecasting using moving average
L_k	ordering lead time for stage k
I_t^k	inventory level of stage k in time period t
q_t^k	order quantity of stage k in time period t without risk pooling
$\overline{q}_t^k$	order quantity of stage k in time period t with risk pooling
$\overline{s}_t^k$	reorder point of stage k in time period t without risk pooling
$\bar{s}_t^k$	reorder point of stage k in time period t with risk pooling.

2.3 Inventory Replenishment Policy

The *retailers* are denoted as stage 0, the *wholesaler* is denoted as stage 1, and the *factory/manufacturer* is denoted as stage 2 in the equations below.

An Event at the beginning of each day synchronizes all supply chain elements, and each supply chain stage checks for orders at the same time, including orders that have just arrived, checks the inventory level, and decides an order quantity, q_t^k. Using similar assumptions to Li et al. (2016) and Lee et al. (2000), we follow the demand assumption that order quantity in the time period, t, depends on the demand from the previous time period, D_{t-1}, and the order-up-to level of the previous two periods.

Initially, the demands are generated from the *customers,* and it is fulfilled from the inventory of the retailers of the supply chain. Stages such as *retailer* and *wholesaler* place orders to the upstream agents. If enough inventory is available, demands from the customer are fulfilled by the retailers instantaneously. For other upstream stages, L_k time is needed to fulfill the order of each downstream stage. The amount shipped is subtracted from the inventory and removed from the ordering queue. The new inventory, I_t^k is calculated by $I_t^k = I_t^k - D_{k,t}$.

If the demand/order is greater than the available inventory, it is shipped to the customer/downstream agent and the remaining demand/order is backlogged, producing a negative inventory level. Backlogs will be addressed when future deliveries are received from the upstream stage of the supply chain. The order-up-to-level policy is used by every stage of the supply chain. For a serial supply chain, a stage calculates the order-up-to level for that period and uses the following equation to calculate the order quantity for that period

$$q_t^k = s_t^k - s_{t-1}^k + D_{k,t-1}.$$

where, q_t^k is the order quantity at time period t for stage k. s_t^k is the order-up-to level for time period t for stage k. The order quantity, q_t^k, relies on demand/order from the previous time period, $D_{k,t-1}$ and on the order-up-to level of the last two time periods. The order-up-to level equation for any stage in time period t is given by:

$$s_t^k = E\left(D_{k,t} + z * \sqrt{Var\left(D_{k,t}\right)}\right),$$

where, $E(D_{k,t})$ is the expected demand/order for periods t to $t + L_k$ of a particular stage k and N is the number of periods to consider for calculating the moving average of demand at time period t. $Var(D_{k,t})$ is the variance of demand for periods t to $t + L_k$ of a particular stage k at time period t. $E(D_{k,t})$ and $Var(D_{k,t})$ are calculated using the following equations.

$$E(D_{k,t}) = \frac{L_k}{N} \sum_{i=t-N}^{t-1} D_{k,i} = \frac{L_k}{N}(D_{k,t-1} + D_{k,t-2} + \dots + D_{k,t-N})$$

$$\begin{aligned} Var(D_{k,t}) &= \frac{1}{N} \sum_{i=t-N}^{t-1} (L_k D_{k,i} - E(D_{k,t}))^2 \\ &= \frac{1}{N}\left[\left(L_k D_{k,t-1} - E(D_{k,t})\right)^2 \dots + \left(L_k D_{t-N} - E(D_{k,t})\right)^2\right] \end{aligned}$$

Each *retailer* and *factory* follow this ordering policy described above. When no information is shared, each stage decides its order-up-to level, which is calculated using the mean and variance of demand/order placed by the downstream stage. However, when information is shared across the supply chain, the actual customer demand information is available to the *wholesaler* and the *factory* also. So, they calculate the order-up-to level using the mean and variance of the actual customer demand.

Four scenarios will be investigated for the *wholesaler* because the *wholesaler* has two *retailers* and the fundamental idea of information sharing and risk pooling can apply at the *wholesaler* stage at the same time. To compare the four different scenarios described above in the introduction (Figures 1-4), we calculate the ratio and difference of variance between the customer demand and order quantity at each stage of the supply chain. Understanding the variance of the order with and without risk pooling is a key difference. The equations below define how the order-up-to level is calculated in the simulation model.

Scenario 1: Without information sharing and without risk pooling:
The order-up-to level for the wholesaler at scenario 1 is as follows:

$$s_t^1 = E\left(D_{R1,t}\right) + E\left(D_{R2,t}\right) + z * \sqrt{Var\left(D_{R1,t}\right)} + z * \sqrt{Var\left(D_{R2,t}\right)},$$

where, $D_{R1,t}$ and $D_{R2,t}$ are the order quantities from retailer1 and retailer2, respectively.

Scenario 2: Without information sharing and with risk pooling:
The order-up-to level for the wholesaler at scenario 1 is as follows:

$$\bar{s}_t^1 = E\left(D_{R1,t} + D_{R2,t}\right) + z\sqrt{Var(D_{R1}) + Var(D_{R2}) + 2\rho_D\sqrt{Var(D_{R1,t})}\sqrt{Var(D_{R2,t})}},$$

where, the orders of the two retailers are correlated with a coefficient $-1 \leq \rho_D \leq 1$.

Scenario 3: With information sharing and without risk pooling:
The same equation of scenario 1 is used but instead of calculating the order-up-to level from the mean and variance of retailer order, the mean and variance of actual customer demand are used.

Scenario 4: With Information Sharing and Without Risk Pooling:
Similarly, the same equation of scenario 2 is used but instead of calculating the order-up-to level from the mean and variance of retailer order, the mean and variance of actual customer demand are used.

In summary, when information sharing is not employed, each stage of the supply chain places orders based on the order quantity received from the downstream agent/stage. However, when information is shared, each agent/stage has access to the actual customer demand, and the order quantity is calculated based on that actual customer demand. For risk pooling, the mean and variance of order quantities of two *retailers* are considered together. Instead of calculating the order-up-to level for each *retailer* separately, the two *retailers* are aggregated statistically together. Consequently, the bullwhip effect is anticipated to be reduced.

2.4 Bullwhip Effect Measurement

While running the simulation, the demand/order placed by each stage to the upstream agent is tracked and the mean and variance of those values are calculated. Two measurements are generally used to measure the bullwhip effect. The first one is the ratio between the variance of order placed by each stage ($Var_{order,k}$) and the variance of actual customer demand (Var_{demand}), which is called the bullwhip effect index, *B*. This measurement is used to measure the magnitude of the bullwhip effect for a particular stage of the supply chain (Chinh et al. 2013).

$$B_{ratio} = \frac{Var_{order,k}}{Var_{demand}}$$

The second metric is the difference between the variance of order placed by each stage ($Var_{order,k}$) and the variance of actual customer demand (Var_{demand}) (Li et al. 2016).

$$B_{difference} = Var_{order,k} - Var_{demand}$$

3 NUMERICAL EXPERIMENTS AND DISCUSSION

To test the performance of the simulation framework and to identify the impact of information sharing and risk pooling in mitigating the bullwhip effect in a generic supply chain, we have considered a three-stage supply chain with a *manufacturer*, a *wholesaler*, and two *retailers*. A custom customer demand distribution is used to generate customer demand for each market. The lead time of fulfilling of an order placed from a retailer to the wholesaler requires one day for the initial experiment. The manufacturer's lead time is one day as well. The *manufacturer* tracks the wholesaler order, and when a manufacturing decision is taken, it takes one day to produce the product and replenish the manufacturer's inventory. Following the policy of Sucky (2009), the safety factor, z = 2.33, is set to meet the desired service level. Like Li et al. (2016), all stages of this supply chain follow a two-period moving average forecasting technique and the same order-up-to policy. Four separate models are built to depict four scenarios.

Initially, all four simulation models are run with a fixed random seed 1 for all four scenarios. At this point, no mitigation strategy is applied. Figure 5 shows the variation of customer demand, total retailer order, wholesaler order, and manufacturer's production quantity with time. The customer demand is relatively stable, but the retailer order quantity is fluctuating and attempting to follow the customer demand pattern. On the other hand, the order quantity of the wholesaler and the manufacturer's production quantity realizes greater fluctuation. Therefore, a strong bullwhip effect is present in this supply chain as no information is shared and risk pooling is not applied by the wholesaler.

Figures 6, 7, and 8 represent the fluctuation of demand/order quantity in the supply chain for scenario 2, 3, and 4, respectively. When no information is shared and risk pooling is applied (scenario 2), the fluctuation in demand/order quantity is reduced substantially as can be seen in Figure 6. Similarly, the bullwhip effect is reduced when information is shared but risk pooling is not applied (scenario 3) as can be seen in Figure 7. Finally, scenario 4 is presented in Figure 8 where the bullwhip effect is reduced the most as the order quantity is not fluctuating significantly throughout the supply chain because both information sharing and risk pooling are present at the same time. Hence, the mitigation strategies appear to work, although the benefits are most effective when the risk pooling and information sharing strategies are applied together.

Each simulation model for all four scenarios is run with random seeds ten times. Then, the variance ratio and variance difference for all stages are calculated. The average value with a 95% confidence interval of ten runs is listed in Table 1. For scenario 1, when no mitigations strategy is applied, the bullwhip effect is high in terms of the variance ratio and variance difference. The variance ratio and the variance difference are higher between *customer* and *factory* but lower between *customer* and *wholesaler*. However, when the first mitigation strategy is applied, scenario 2: without information sharing and with risk pooling, the average reduction in variance ratio is 33.23% for the *customer-factory* pair and 19.42%

for the *customer-wholesaler* pair. Similarly, the average reduction in variance difference is 48.40% and 38.42% for the *customer-factory* and *customer-wholesaler* pairs, consecutively. The bullwhip effect is reduced for scenarios 3 also. However, the highest average reduction is seen when centralized information and risk pooling are applied at the same time (scenario 4). As compared to scenario 1, in which risk pooling and information sharing are not used in the supply chain, the average reduction in variance ratio for the *customer- factory* pair is 46.32% and 49.27% for the *customer-wholesaler* pair. In addition, the difference between variances is also reduced by 61.68% and 65.48%, respectively.

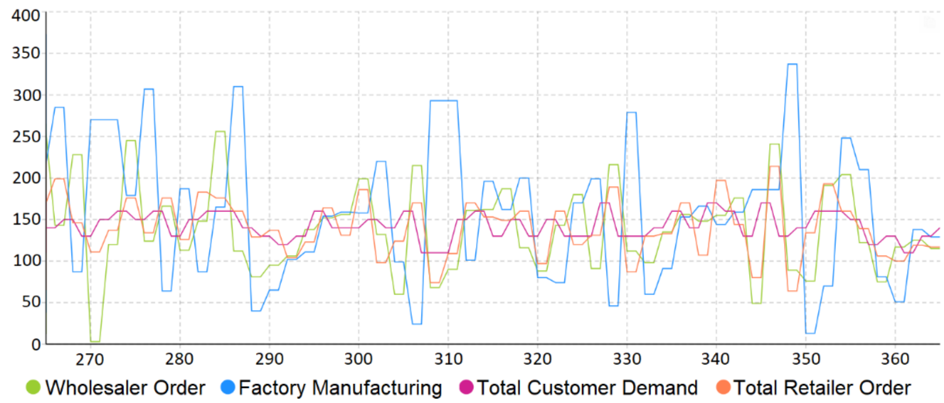

Figure 5: Demand/order variability with time (scenario 1: without information sharing and without risk pooling).

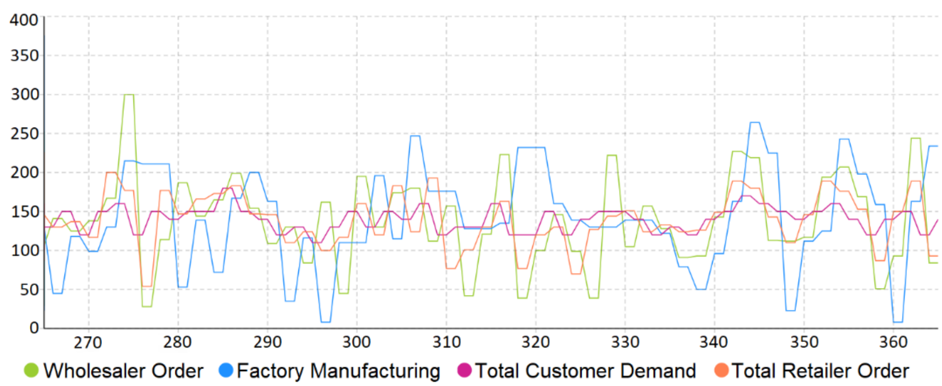

Figure 6: Demand/order variability with time (scenario 2: without information sharing and with risk pooling).

Figure 9 depicts the percentage of variance ratio reduction, with a 95% confidence interval, by both mitigation strategies (scenario 4) with an increase in lead time. We considered deterministic lead times, and the values are 1, 2, 3, and 5, respectively. Even with an increase in lead time, the percentage of variance ratio reduction is significantly high and increases as well. The confidence interval is also small and decreases with increasing lead time. Therefore, the coupled effect of both strategies does not deteriorate even in higher lead times. Moreover, the percentage of variance ratio reduction considering stochastic lead time is showed in Figure 10 with a 95% confidence interval. Here, the lead times follow a discrete uniform distribution. We have considered three lead time distributions as *unif_discr* (1,2), *unif_discr* (1,3), and *unif_discr* (1,5), respectively. The results show that the percentage of variance ratio reduction is also increasing even if lead time distributions with increasing ranges are used during the simulation. The confidence interval is also small similar to the deterministic case. For both deterministic and stochastic cases, the variance ratio reduction ranges from 75 to 99%, which is comparable with the results of Li et al. (2016), where the variance ratio reduction is 96.7% for scenario 4 of their study. Finally, it is evident that when both strategies are used, the bullwhip effect is significantly reduced albeit of larger lead limes for both deterministic and stochastic cases.

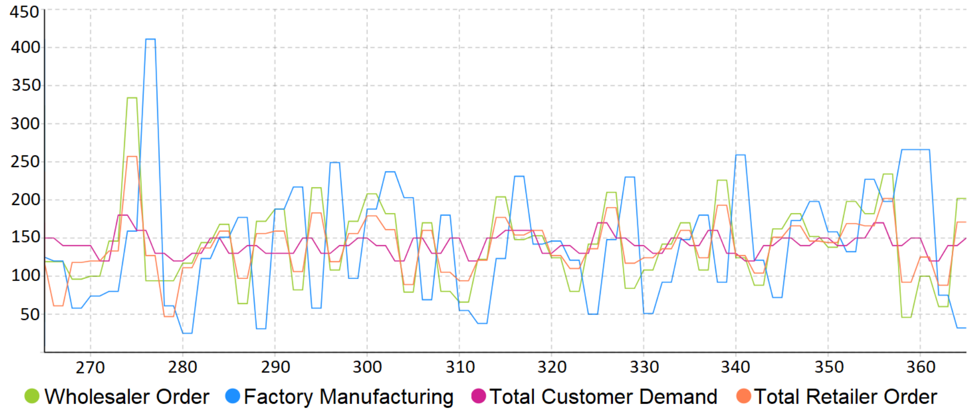

Figure 7: Demand/order variability with time (scenario 3: with information sharing and without risk pooling).

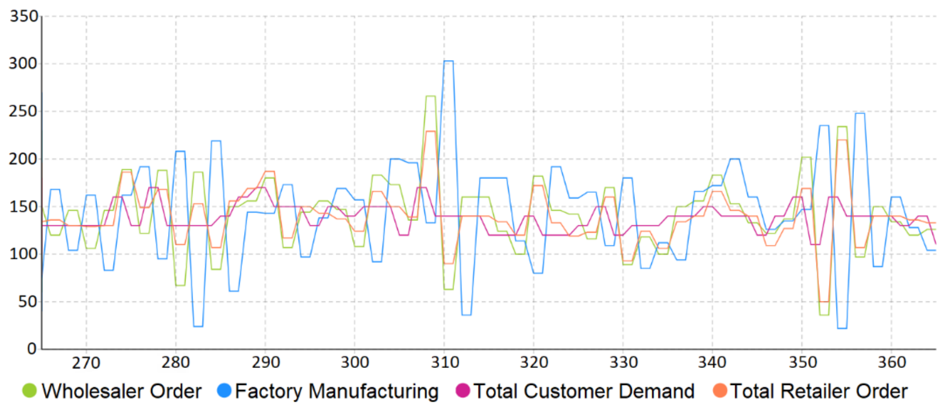

Figure 8: Demand/order variability with time (scenario 4: with information sharing and with risk pooling).

Some managerial insights can be drawn from the above results. First, information should be shared between all stages of the supply chain. The *customer* demand information should be available to the *wholesaler* and the *manufacturer* instantly. If direct access to the customer demand data is instantly available to the *wholesaler* and the *manufacturer*, they can easily take their ordering decision with less forecasting error, which will reduce the inventory cost and overproduction. If actual customer demands are available to the *wholesaler* and the *manufacturer*, they will be able to adapt their marketing strategy and make decisions that are more market-driven as well as data-driven. Second, all the parties can work together in a way where they are not only working to increase their profit but also to increase the total profitability of the supply chain. Third, from modeling perspective, the simulation-based approach to study the bullwhip effect is shown to be efficacious because more practical and complex supply chains can be easily modeled using this technique to handle stochasticity and nonlinearity, from which other methods often suffer.

Table 1: Variance ratio and variance difference between supply chain stages.

Variance Ratio				**Customer-Factory**	**%Decrease**	**Customer-Wholesaler**	**%Decrease**
Scenario	1	Decentralized Information	w/o Risk Pooling	16.20±1.69	-	9.48±0.65	-
	2		w/ Risk Pooling	11.10±0.93	33.23±8.93	7.74±0.46	19.42±7.46
	3	Centralized Information	w/o Risk Pooling	12.3±1.42	24.51±12.59	6.80±0.77	27.22±11.47
	4		w/ Risk Pooling	8.49±0.66	46.32±7.44	4.77±0.46	49.27±6.33
Variance Difference							
	1	Decentralized Information	w/o Risk Pooling	9,379.93±1213.57	-	5,242.66±539.32	-
	2		w/ Risk Pooling	4,840.50±425.99	48.40±12.43	3,228.52±192.46	38.42±7.46
	3	Centralized Information	w/o Risk Pooling	5,425.64±651.68	42.16±12.60	2,788.17±375.05	46.82±11.47
	4		w/ Risk Pooling	3,594.39±317.76	61.68±7.41	1,809.58±218.93	65.48±7.00

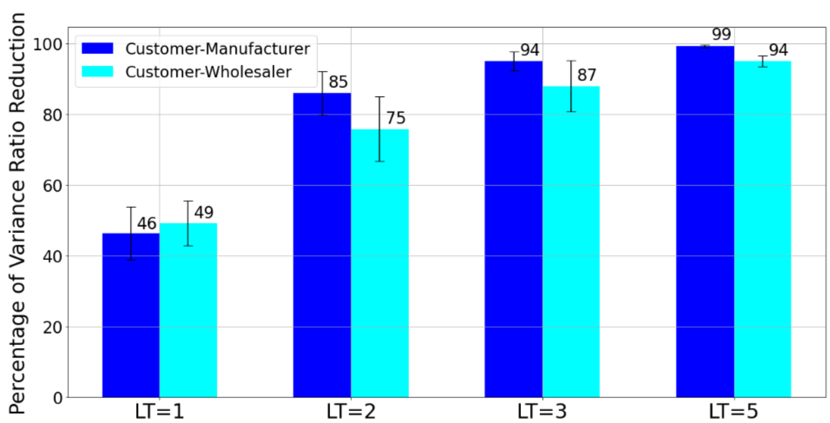

Figure 9: Variance ratio reduction at scenario 4 with deterministic lead time.

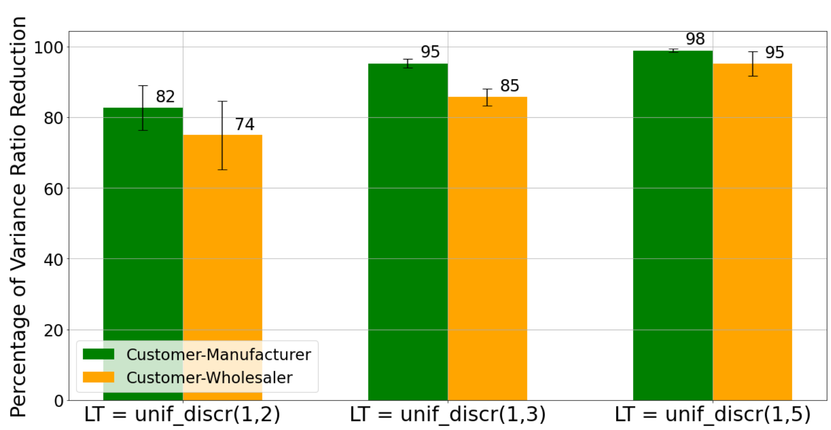

Figure 10: Variance ratio reduction at scenario 4 with stochastic lead time.

4 CONCLUSION

An agent-based simulation model is developed in this work to measure the bullwhip effect in a supply chain and to investigate different strategies, specifically information sharing and risk pooling, to mitigate the impact from the bullwhip effect. Four scenarios have been considered combining the presence and absence of risk pooling and information sharing. The proposed agent-based simulation model was used to conduct a numerical study of a three-stage supply chain. The bullwhip effect for four different scenarios was measured and compared. Simulation results show that information sharing and risk pooling can reduce the bullwhip effect in a supply chain when applied separately as well as simultaneously. When information sharing and risk pooling are applied at the same time, numerical results show greater variance reduction. With an increase in deterministic lead the combined strategies show significant and increasing reduction in variance with reasonable confidence interval. The variance reduction is also high when stochastic lead time is used. The wider the range of the values of discrete uniform distribution of lead time, the higher the percentage of variance reduction. Therefore, risk pooling and information sharing strategies works well together even in the case of larger and stochastic lead times. This agent-based simulation framework can be extended to study complex model configurations, for example, under situations where customer demands can be directly fulfilled from the wholesaler and manufacturer. Future research could also consider, disruptions in the supply chain, order split in wholesaler and manufacture, and so on.

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