IMPACT OF RETURN FLOW ESTIMATION WITH ORBIT INFORMATION ON THE BULLWHIP EFFECT IN A MULTI-ECHELON CLOSED-LOOP SUPPLY CHAIN WITH PRODUCTION CAPACITY

by

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ABSTRACT

IMPACT OF RETURN FLOW ESTIMATION WITH ORBIT INFORMATION ON THE BULLWHIP EFFECT IN A MULTI-ECHELON CLOSED-LOOP SUPPLY CHAIN WITH PRODUCTION CAPACITY

Closed-loop supply chains recover used products and reduce material use and waste through remanufacturing. However, uncertainties in the return flow propagate through the supply chain, especially in multi-echelon systems. Return variability amplifies the order and inventory fluctuations upstream, also known as the bullwhip effect phenomenon. In this study, we analyze a multi-echelon closed-loop supply chain with production capacity, where the customer demand for a single type of product is met by manufacturing new products and remanufacturing returned cores. A single retailer, wholesaler, distributor, and OEM replenish their inventory with (r, S) periodic review. Effective return estimation is necessary to mitigate the bullwhip effect. Traditional forecasting methods such as the moving average and exponential smoothing disregard the correlation between past sales and future returns. To this end, we utilize information on the orbit size, expected product lifetime, and return probability to estimate returns. Then, we analyze the impact of return estimation with orbit information on the bullwhip behaviour under various factors such as return probability, reorder period, and average product lifetime. We compare the bullwhip behaviour in the forward supply chain with the closed-loop supply chain under different return estimation methods. We also introduce alternative shipment policies to reduce the delivery lead time, and investigate the impact of impulse demand. We observe that closed-loop supply chains with production capacity constraint exhibit different bullwhip behavior than the uncapacitated systems.

ÖZET

ÜRETİM KAPASİTELİ ÇOK KATMANLI KAPALI DÖNGÜ TEDARİK ZİNCİRİNDE KULLANIMDAKİ ÜRÜN BİLGİSİYLE GERİ DÖNÜŞ TAHMİNİNİN KAMÇI ETKİSİ ÜZERİNE ETKİSİ

Kapalı döngü tedarik zincirleri, yeniden üretim yoluyla ürünleri geri kazanır, malzeme kullanımını ve israfı azaltır. Ancak geri dönüş akışındaki belirsizlikler özellikle çok katmanlı sistemlerde dalgalanmaların tedarik zincirinde artarak ilerlemesine sebep olur. Talep ve geri dönüş değişkenliği, ya da kamçı etkisi, tedarik zincirinde yukarı yönde artar. Bu çalışmada, tek tip ürüne yönelik kullanıcı talebinin yeni ürünler üretilerek ve geri dönen ürünlerin yeniden üretilerek karşılandığı, üretim kapasitesine sahip, çok katmanlı kapalı döngü tedarik zinciri analiz edilmektedir. Tek bir perakendeci, toptancı, distribütör ve üretici, envanterlerini (r, S) periyodik incelemeyle yeniler. Yukarı yönlü sipariş ve talep değişkenliğindeki artışı azaltmak için etkili geri dönüş tahmini gereklidir. Hareketli ortalama ve üstel düzeltme gibi geleneksel tahmin yöntemleri, geçmiş satışlar ile gelecekteki geri dönüşler arasındaki korelasyonu göz ardı eder. Bu amaçla, geri dönüşleri tahmin etmek için kullanımdaki ürün sayısı, beklenen ürün ömrü ve geri dönüş olasılığı hakkındaki bilgilerden yararlanıyoruz. Daha sonra, iade olasılığı, yeniden sipariş süresi ve ortalama ürün ömrü gibi çeşitli faktörler altında kullanımdaki ürün bilgileriyle iade tahmininin kamçı davranışı üzerindeki etkisini analiz ediyoruz. Tek yönlü ürün akışı olan tedarik zincirindeki kamçı etkisini, farklı geri dönüş tahmin yöntemleri altında kapalı döngü tedarik zinciriyle karşılaştırıyoruz. Ayrıca teslimat süresini kısaltmak için alternatif sevkiyat politikaları uyguluyoruz ve anlık talebin tedarik zincirine etkisini araştırıyoruz. Üretim kapasiteli kapalı döngü tedarik zincirlerinin, kapasitesiz sistemlerden farklı kamçı davranışı sergilediğini gözlemliyoruz.

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LIST OF SYMBOLS

C	Production Capacity
$\bar{D}$	Estimated demand
D_t	Daily demand at time t
k	Echelon *or* scale parameter of Weibull
L	Lead time
$\bar{L}$	Estimated lead time
L_m	Manufacturing lead time
L_r	Remanufacturing lead time
m	Number of moving average periods
n	Number of shipments
OQ	Order quantity
OS_t	Orbit size at time t
p	Return probability
PQ	Production quantity
R_t	Returns during reorder period at time t
$\bar{R}$	Estimated return
r	Reorder period
S	Order-up-to point
${s_D}^2$	Estimated variance of daily demand
${s_R}^2$	Estimated variance of returns
${s_X}^2$	Estimated variance of lead time demand
SS	Safety stock
T	Order cycle time
X_t	Lead time demand during reorder period at time t
z_α	Safety factor
γ	Average product lifetime
λ	Daily demand rate

μ	Mean
${\sigma_D}^2$	Demand variance
${\sigma_{O_k}}^2$	Order variance of echelon k

LIST OF ACRONYMS/ABBREVIATIONS

AFR	Average Fill Rate
ANOVA	Analysis of Variance
ARI	Advanced Return Information
BWE	Bullwhip Effect
CLSC	Closed-Loop Supply Chain
CV	Coefficient of Variation
DIST	Distributor
DSL	Desired Service Level
FR	Fill Rate
FSC	Forward Supply Chain
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
ICT	Information and Communication Technology
IP	Inventory Position
MA	Moving Average
NS	Net Stock
NSA	Net Stock Amplification
PLD	Product Lifetime Distribution
RET	Retailer
RFID	Radio Frequency Identification
OEM	Original Equipment Manufacturer
OS	Orbit Size
WHSA	Wholesaler
WIP	Work in Progress

1. INTRODUCTION

Supply chain operations are an integral part of most businesses and industries while bearing an important portion of the organizational difficulties. Managing the supply chain complexity leads to better supply chain performances [1], and helps achieve customer satisfaction, competitive advantage, and reduced costs. Resource, raw material, and energy related supply chain risks and environmental concerns unveiled the growing need to transition to a more sustainable system. Reverse logistics has emerged as a concept to address sustainability issues. The traditional supply chain, as seen in Figure 1.1, fails to recognize waste management and product/material recovery. The movement of material and products from the end users to the point of origin, if planned and controlled efficiently, can recapture or create value, and ensure proper disposal [2]. The process of product returns, recycling, repairs, recovery, and waste disposal is covered by reverse logistics, as seen in Figure 1.2.

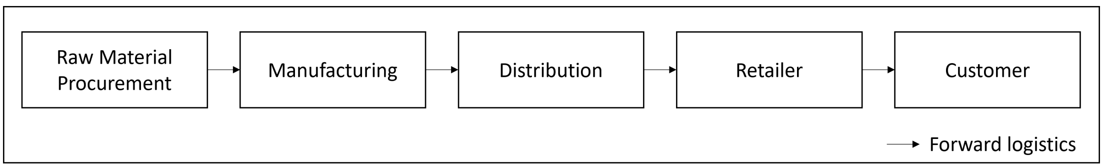


Figure 1.1. Traditional forward supply chain.

Although the regulations or pressure from the environmental groups is considered to be the main driver for the reverse supply chain practices, most of the firms realized reverse logistics provides strategic, competitive, and financial benefits [3]. Customers prefer buying from companies that accept returns to reduce risk, and companies can recover value and reduce landfill costs. Following public awareness, European legislation started to enforce mandatory requirements on the collection and recycling of electronic goods [4], with Japan, China, Canada, and the US following [5]. Apart from the environmental benefits, companies discovered the commercial opportunities of CLSCs as a profitable value recovery and a new revenue flow along with cost reduction [6]. Electronic devices that contain hazardous materials can be recycled or disposed of safely via take-back programs, and industry leaders such as Apple, Dell, and Sony began implementing recovery programs voluntarily [7]. AT&T, Hewlett Packard, and Xerox have been taking initiatives to grow return flow not only to reduce costs but establish new sources of profit [8].

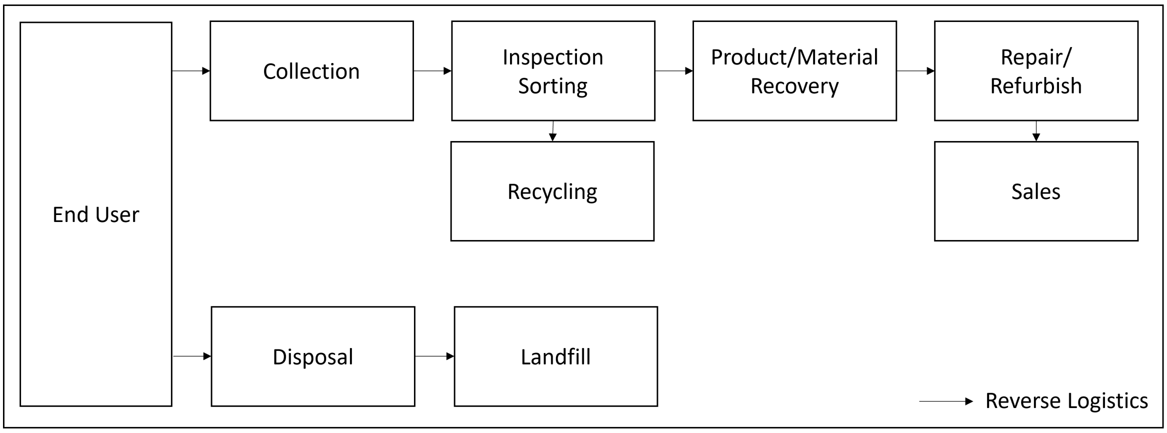


Figure 1.2. Reverse logistics.

Closed-loop supply chains integrate the one-way flow of forward and reverse logistics by reintroducing used products or materials as a resource. Remanufacturing and recovery operations can generate additional value from the returned products and prevent material waste. The reverse flow of typical closed-loop supply chain activities starts with the collection of used, defective, or obsolete items from retailers or consumers. The processing of returned products depends on inspection and sorting. Companies may opt to reuse and resell products in good condition. If the product is to be refurbished, the specified quality level must be monitored in order to ensure extended service life. Remanufacturing may involve repairs or material recovery for production. Recycling is treated as a last resort to retrieve value from the reverse flow.

In addition to the uncertainties and need for demand forecasting in traditional one-directional supply chains, closed-loop supply chains must handle the timing and quantity of returns. The Bullwhip effect, namely the phenomenon of demand amplification from downstream to upstream echelons, becomes a bigger threat to the stability of the supply chain network due to the additional uncertainty brought by the return flow. Successful supply chain operations and customer service rely on identifying the causes of demand variability and mitigating its consequences [9].

The orbit, namely the products in use, provides information on the quantity of future returns. Information on the expected product lifetime and the number of products in use can be utilized to estimate returns more accurately. This study models the orbit-based return estimation and forecasts returns with the orbit size and product lifetime distribution.

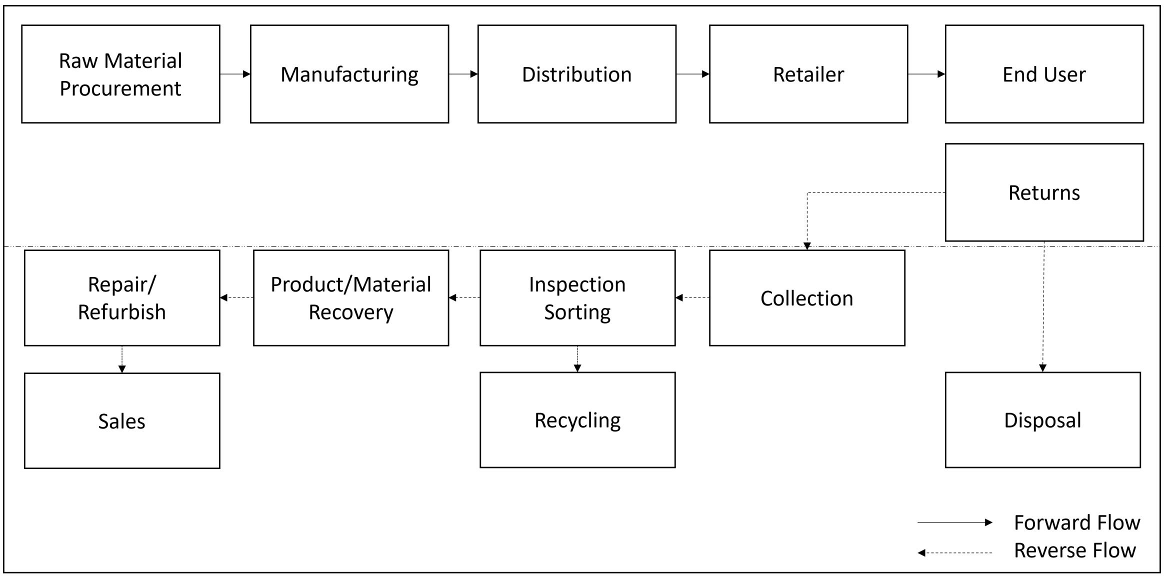


Figure 1.3. Closed-loop supply chain with forward and reverse product flow.

In this study, we explore the contribution of various supply chain factors to the bullwhip effect. We formulate a multi-echelon closed-loop supply with production capacity constraints consisting of a single retailer, wholesaler, distributor, OEM, and the orbit to analyze the causes of the bullwhip effect. Utilizing a discrete-event simulation model, we experiment with several parameters such as reorder period, return probability, and average product lifetime to determine their effect on order volatility. We investigate the impact of the return estimation accuracy on the bullwhip effect in the closed-loop supply chain and construct a return estimation method utilizing the orbit information to observe its advantages over the moving average forecasting. Finally, we analyze the closed-loop supply chain under impulse demand with three return estimation methods: the moving average, orbit size information, and advance return information.

Before presenting the results of our numerical analysis and experiments with various parameters, we outline the previous research in the literature review and explain our methodology, assumptions, and simulation model in detail. Finally, we describe our main findings and future research in the conclusion chapter.

2. LITERATURE REVIEW

In this section, we survey the existing research on closed-loop supply chains (CLSC) and the bullwhip effect to explore the gaps in research related to the use of orbit information in return estimation and capacitated production. We present the theoretical background in the literature, discuss the scope and outcome of the previous studies, and demonstrate the gaps in the field that we seek to address in this study.

We first review the CLSC system, a supply chain operation with forward and reverse product flow. Secondly, we analyze the context, causes, and impact of demand amplification, namely the Bullwhip Effect (BWE), and evaluate the strategies developed to mitigate this phenomenon. We then assess the related studies on the value of information in supply chains. Finally, we outline the research background on customer loyalty and its impacts on supply chain operations.

Originally coined as “demand amplification” by Forrester [10] and later as the “bullwhip effect” [11], the increase of order variability upstream in multi-echelon supply chains has been one of the longstanding problems in supply chain management. The dynamic behavior of the multi-echelon systems has been investigated under common assumptions such as backlogging the unmet demand and deterministic or stationary stochastic demand (i.e. demand pattern with a stationary long-term mean) as it is not possible to calculate the demand amplification of a non-stationary demand [12].

Researchers analyze the bullwhip effect with three different approaches: the discrete time approach, the continuous time approach, and the control theory approach [12]. The discrete time approach uses discrete time intervals, namely the ordering and production plans are made in intervals even if the customers purchase products within the interval. The continuous time approach continuously observes the system and focuses on the rates of flow. Continuous time models are common in the system dynamics field. Finally, the control theory approach is based on the linear systems of transfer functions and may use either discrete or continuous time. The transfer function refers to the relationship between the input and output of the system.

The bullwhip effect literature has been divided into six stages by Holweg and Disney [12]: the production and inventory control era before 1958, the production smoothing era between 1958 and 1969, the development of control theory between 1970 and 1989, the "Beer Game" phase between 1989 and 1997, the bullwhip rediscovery phase between 1997 and 2000, and the bullwhip avoidance phase since 2000.

Lee *et al.* [11] analyzed the four sources of information distortion: demand signal processing, rationing game, order batching, and price variations. They argue that not using past demands for forecasting, infinite resupply with a fixed lead time, no fixed order cost, and stationary purchase cost result in the same variance for the orders and demand. Relaxing each of these conditions causes the aforementioned sources of the bullwhip effect. Demand signal processing corresponds to non-stationary demand and demand forecasting with past demand information. The rationing game is the strategic ordering behavior when buyers anticipate a supply shortage. Order batching becomes an economical strategy when the order cost is nonzero. Finally, price variations refer to the non-stationary purchase cost.

CLSCs deal with the collection and recovery of end-of-life products along with the forward product flow [13]. Compared to the traditional supply chain, CLSCs face uncertainty from the product return flow along with the demand. The theoretical assumption is that uncertainty cannot be eliminated, and the decision-making processes should focus on reducing the negative consequences instead [14]. On the contrary, there are researchers who suggest utilizing demand information to diminish uncertainties [15].

Yang *et al.* [16] developed a general CLSC model with raw material suppliers, manufacturers, retailers, consumers, and recovery centers. They showed the effects of parameters such as the return ratio, transformation rate of raw materials, and transformation rate of recyclable products to determine the optimal state of the network.

Kannan *et al.* [17] analyzed a closed-loop supply chain model with four echelons in terms of cost minimization. With a deterministic demand, the reverse logistics operation was found to be more beneficial to the customer. However, these studies assumed uncapacitated production.

Lin *et al.* [18] analyzed the bullwhip effect in a closed-loop supply chain with a discrete time series model to show the impact of demand forecasting on the bullwhip effect. They argue the lead time causes bullwhip only when it is coupled with demand forecasting. They constructed a closed-loop supply chain model with four echelons, but only the impact of demand estimation is modeled whereas the return estimation is omitted. Production capacity was not taken into account.

Huang and Liu [19] modeled a supply chain with the manufacturer, distributor, and retailer to compare the bullwhip effect and inventory variance in the forward and closed-loop supply chain with different return rates and manufacturing lead times. They showed that the bullwhip effect in a closed-loop supply chain is greater than the initial forward supply chain regardless of the collection rate. They included manufacturing and remanufacturing constraints but did not consider the impact of return estimation.

On the contrary, Qingli *et al.* [20] found that remanufacturing reduces the bullwhip effect when the returns are included in the forward flow instead of a secondary reuse market. They modeled a supply chain with a producer, distributor, and retailer. The remanufacturer and collector operate independently. The remanufacturing system has a capacity but this study did not take return estimation into account.

In addition to issues with the supply of cores suitable for remanufacturing, forecasting the product return is a critical concern. Product failure is mostly a random process and remote monitoring of electronic products has been suggested to manage the recovery process [21]. ICT systems arguably reduce the uncertainties related to the status of the returned cores.

Carrasco-Gallego and Ponce-Cueto [22] reviewed the return forecasting models and proposed a model that does not require product-level information. In a traditional supply chain, only the future demand is estimated using past sales. Unlike the one-way supply chain, CLSC planning requires forecasts on both future demand and returns. A common approach to returns forecasts is utilizing historical return series when it is the only information available. However, this method ignores past sales information which is relevant to the future returns. Since the past sales are expected to generate future returns after the product's time in the market is completed. The authors introduced a dynamic regression model for return forecasting which uses sales information as the input series and return information as the output series. They argue that this method ceases the need for tracking devices to estimate returns.

Dev *et al.* [23] compared the inventory and production planning under continuous and periodic review. Remanufacturing lowered the order fluctuations in the periodic review system, and there was a trade-off between demand, lead time, and reorder periods. Higher values of the reorder period and return to demand rate led to the periodic review system outperforming the continuous review system.

Chen *et al.* [24] quantified the demand amplification in a two-tier supply chain with a single retailer and a single manufacturer. They extended the results to multi-tier supply chains and showed that the bullwhip effect can be reduced but not eliminated by using centralized demand information, namely making the customer demand information available to all tiers of the supply chain. Even if each stage of the supply chain has complete demand information, the bullwhip effect will persist.

Several studies explored the impact of increasing the product return rate to mitigate the bullwhip effect in CLSCs [25–28]. Zhou and Disney [27] showed that the large return rates dampened demand fluctuations, thus reducing the bullwhip effect and the inventory variance. They also found that the supply chains with returns always have less bullwhip and inventory variance compared to supply chains without returns. Their results highlight the importance of returns even when the rate is small.

Yuan and Zhang [29] modeled a supply chain model with a supplier, manufacturer, two retailers, and a recycler. They showed that the higher product return rate increases the proportion of recycling in production, and the order fluctuation will decrease as a result. Increasing recycling lead time caused rising manufacturer order quantity, but the retailer order fluctuation saw little change. Corum *et al.* [30] considered production order variance and total recoverable and serviceable inventory costs as main performance indicators. They found that the pull-control policy (i.e., production quantity is based on customer demand) outperformed the push-control system (i.e., forecasting the inventory before customer demand arrives).

Adenso-Diaz *et al.* [31] analyzed the main factors affecting bullwhip in reverse supply chains. They extend on the Beer Game to a closed-loop supply chain to investigate the impact of factors established in the forward chain research on reverse logistics. They observed a significant influence of the factors considered, such as customer demand variability, information sharing, and forecasting technique, confirming the factors affecting the forward chain also affect the reverse chain. Among the factors specific to the reverse supply chain, only the percentage of units returned had a significant influence. Average product usage time and recycling capacity did not seem to affect the bullwhip effect. The product usage time is modeled as a random variable with two levels, 15 and 60 weeks, and was not factored in a return estimation process.

Cachon *et al.* [9] analyzed the strength of the bullwhip effect across different industries. They found that the wholesale industries are prone to demand variability, but the retail and manufacturing industries are not. They also argued that the bullwhip effect is more prominent with nonseasonal demand and the highly seasonal industries tend to smooth demand variance. Seasonal industries could practice production smoothing by producing at consistent levels, accumulating inventory during the low season, and supplying from the built-up inventory during the high season.

Several studies made efforts to optimize production quantities in order to lower costs [32–34]. The common assumptions were that production is smoother than consumption, and inventory has a negative correlation with customer demand. Although these studies argued that the leveled production with inventory as a buffer could limit the amplification, many empirical studies found that the inventory is positively correlated with customer demand [35–37]. The inventory levels had a destabilizing influence, causing the production variance to be greater than the demand variance.

Ponte *et al.* [38] analyzed the impact of capacity constraints in the order-up-to replenishment policy under random demand. They observed the smoothing mechanism of capacity constraint on the production, but the opposite impact on the inventory variability. They also suggested that the capacity constraint had positive economic outcomes as it can reduce costs. They provided an optimal capacity calculation given the demand, unit costs, and lead time. However, the results and solutions only apply to the manufacturers as this study analyzes only a single supply chain echelon. The impact of capacity constraint on downstream remains to be explored.

Inventory replenishment policies are considered to induce the bullwhip effect [39]. Forecasting future demand intensifies order variability, and using appropriate replenishment policies helps mitigate the consequences of the bullwhip effect. Demand amplification was found to be inevitable with the order-up-to policy. However, the order-up-to policy minimizes the inventory holding and stock-out costs. The bullwhip effect was effectively dampened with simple exponential smoothing.

Supply chains are complex systems with a network of various actors and activities, from raw material procurement to customer delivery. Each actor operates on a different set of constraints and objectives, but their performance relies on interdependent processes [40]. Hence, coordination is a key element of successful supply chain management [41]. Information sharing is highlighted as a solution to dampen the demand amplification [42].

The focus of information sharing in supply chains has been sharing the customer demand or its forecast [43–45]. Exchanging demand information was found to be more effective in reducing BWE than order smoothing [46]. A system dynamics simulation showed the effectiveness of information sharing to inhibit fluctuations [45]. However, the impact of information sharing was found to depend on the type of information [47, 48].

Jeong and Hong [49] investigated the impact of information sharing on BWE with a four-echelon supply chain model where each echelon shares some of the customer demand forecast with the lowest echelon, namely the retailer. They found that the higher information sharing rate reduced the BWE significantly, but a highly unbalanced information sharing rate caused reverse BWE. They define reverse BWE as the demand amplification downstream instead of the expected upstream increase in the bullwhip effect. The impact of the information sharing rate was also different at each echelon. On the contrary, Raghunathan [50] showed that the manufacturer's benefit from the information sharing is insignificant when the demand is non-stationary. They argued the manufacturer could reduce the variability by using the entire order history instead of an inter-organizational information sharing system.

As for information sharing in CLSCs, sharing return and yield information was found to be beneficial to the manufacturer in some cases, while the production variability increased in certain scenarios [51]. Advance notice of returns reduced the inventory variance when the manufacturing and remanufacturing lead times are identical. Another study showed that the return information is valuable even when the return rates are small [52]. However, these studies model a two-tier supply chain.

Although the bullwhip effect in the closed-loop supply chain has been studied extensively, the studies mostly limit the size of the chain, omit production capacity, and most importantly do not explore the impact of the orbit information on the return estimation. In this study, we aim to analyze the bullwhip effect in a multi-echelon closed-loop supply chain with production capacity to investigate the impact of return estimation with orbit information.

3. PROBLEM STATEMENT

Although the bullwhip effect and reverse logistics have been areas of interest in supply chain research, studies mostly model uncapacitated production. In this study, we analyze a multi-echelon closed-loop supply chain with a production capacity constraint to achieve more realistic results. The capacity constraint limits the production flow and affects the delivery lead times, inventory levels, and ultimately the return quantity back into the forward flow through remanufacturing.

Information in the supply chain has been found to reduce the bullwhip effect. However, the previous studies utilize information to forecast customer demand. The return flow is correlated with past sales and traditional return estimation methods such as the moving average and exponential smoothing do not take the relationship between sales and returns into account. We introduce a return estimation method with orbit information as a function of the number of products in use, expected service life, and the return probability. The return estimation with orbit information is utilized by the OEM to make production decisions.

We hypothesize that the orbit information can provide more accurate return forecasts. To this end, we compare the forward supply chain with the closed-loop supply in three return estimation scenarios: moving average, orbit information, and advanced return information. Finally, we observe the significance of the return estimation method in the closed-loop supply chain under impulse demand.

4. METHODOLOGY

This chapter presents the research design, the description of the model, the data analysis method, and the verification of the simulation model. We utilize discrete-event simulation modeling to depict the research problem, compare various settings, and draw inferences regarding the capacitated closed-loop multi-echelon supply chain systems. We describe our conceptual CLSC model and address the research problem, explain the analysis of simulation output with the batch means method, and finally, verify and validate our simulation model with various tests to ensure an accurate representation of the conceptual model. We analyze the batch means of order and inventory variability, fill rate, order cycle time, and capacity utilization at steady state using the data collected with the batch means method after discounting the warm-up period.

4.1. Research Design

Discrete-event simulation has been a prevalent tool to analyze logistics and supply chain-related problems. Supply chain systems are challenged with different sources of uncertainties, and therefore, the ability of simulation to investigate complex stochastic processes makes simulation an effective research tool [53]. As we are investigating events in a multi-echelon closed-loop supply chain, mathematical models such as queueing networks could be too complex to solve and not as flexible as a simulation to explore ‘what-if’ scenarios.

The research structure of this study consists of two phases. We first conceptualize the problem, develop and verify the simulation model. We then experiment with different inventory replenishment policies to analyze the impact of the model parameters on the bullwhip effect. After outlining the assumptions and limitations, we specify the model characteristics which will be explained in detail later in this chapter. Then, we develop the simulation model with Python programming language. Figure 4.1 demonstrates the product and information flow in the multi-echelon closed-loop supply chain structure we consider.

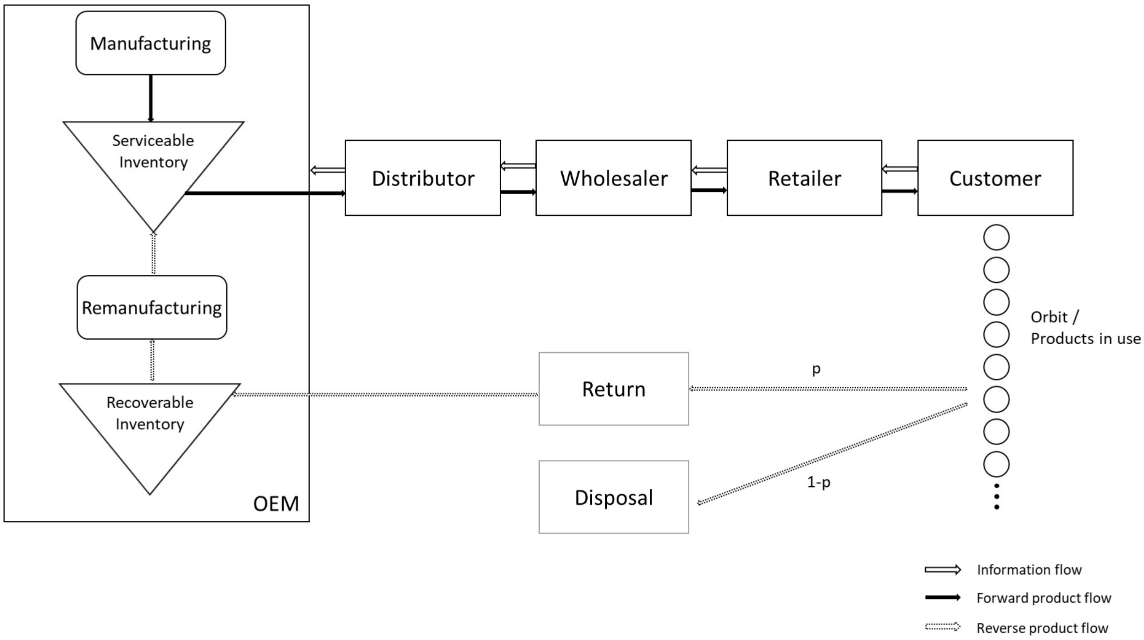


Figure 4.1. Information and product flow in the multi-echelon closed-loop supply chain model.

4.2. Description of the Model

In this study, customer demand for a single type of product is met through a multi-echelon production system with make-to-stock inventory using periodic review, where supply is made up of either newly manufactured products or remanufactured returned items. Remanufactured products are assumed to be indistinguishable from the new products, and customer demand is met with a single stream of inventory. The OEM has manufacturing capacity constraints, limiting the ability to meet demand on time.

The supply chain model does not imply a specific industry and can be adapted for a wide range of products with different demands and expected service lives. The supply chain consists of the OEM, distributor, wholesaler, retailer, and customer, which respectively manufactures (and remanufactures), distributes, wholesales, sells, and buys a single type of product. Each node orders strictly from the upper echelon. Echelons are composed of a single OEM, distributor, wholesaler, and retailer, hence, there is no competition or cooperation between actors in the same echelon present in the model.

The multi-echelon CLSC model consists of four echelons, namely the retailer, wholesaler, distributor, and OEM, or echelons 1, 2, 3, and 4 respectively. Customer demand follows independent exponential interarrival times with a daily rate of λ and arrives at the retailer one at a time. The exponential distribution is a reasonable choice for modeling interarrival times, given the large coefficient of variation [54]. If the retailer has stock on hand, customer demand is met, and the product's service life begins. When the retailer encounters stock-outs, the demand that cannot be fulfilled is lost as the retailer does not practice back-ordering. The products' service time follows an exponential rate γ, and end-of-life products are either returned to OEM with probability p or discarded with probability $1 - p$. Product usage rates are independent. The returned items are collected in the recoverable inventory.

The production capacity for new products is fixed and higher than the expected customer demand per reorder period (i.e., OEM's utilization for new product manufacturing is less than 1) to ensure that the order backlog remains finite. Remanufacturing is uncapacitated and returned items are stored in recoverable inventory until being remanufactured with a fixed lead time and are transferred to the serviceable inventory. All returned products are assumed to be recoverable, with no limit to how many times a product can be remanufactured. However, once a product is disposed of, it leaves the supply chain permanently.

The periodic review policy (r, S) is used in the simulation model where an order is placed to the immediate upper echelon to replenish the inventory to the order-up-to level S at every r time intervals. The order-up-to level S is dynamic and updated at each reorder point. At the reorder time t, each echelon makes order decisions based on the previous order information from the most recent order at time $t - r$ to the oldest at time $t - m \cdot r$, averaging the latest m orders. To elaborate the replenishment process in more detail, the retailer estimates the upcoming customer demand using the moving average of the customer order history and updates its order-up-to level, then places a replenishment order to the wholesaler with the amount of the difference between its order-up-to level and inventory position. Since the retailer does not accept back orders, its inventory position is equal to the sum of its on-hand inventory and on-order inventory expected to be delivered by the wholesaler. The wholesaler and the distributor follow the same demand forecasting and inventory replenishment process as the retailer, with the distinction of backorders. When the order quantity is greater than the net stock, the wholesaler and distributor withhold the order until the complete order quantity is available in the base policy of the model. The order delivery process consists of order preparation and shipment. The shipment process takes place with constant lead time, whereas the order preparation process could be prolonged due to the lack of available stock. Since the order delivery process starts when the order is placed, the delivery lead time L is at least as much as the shipment lead time, extending with the order preparation process.

Similar to the lower echelons, OEM uses moving average forecasting to determine produce-up-to level S by reviewing order history, as well as the previous returns. Since OEM satisfies demand with either new production or remanufactured returns, the remanufacturing estimation is deducted from the produce-up-to level. The new production quantity is determined as the produce-up-to level minus the inventory position, bounded by the predetermined and constant manufacturing capacity. OEM's inventory position is the sum of the on-hand inventory and the work-in-progress (WIP) inventory. WIP includes the new production with manufacturing lead time L_m and remanufacturing with remanufacturing lead time L_r. Remanufactured items are moved from the recoverable inventory to the serviceable inventory, where the new products are also stored as finished goods. OEM fulfills back orders with the same process as the wholesaler and distributor.

We demonstrate the computational steps of the inventory replenishment process in depth. Let D be the daily customer demand with the exponentially distributed interarrival rate λ (i.e., $D \sim Pois(\lambda)$). The retailer estimates the cumulative demand at the reorder point r and the delivery lead time L. This is the observed demand that includes lost sales and fulfilled demand. Let X_t be the lead time demand observed over the period of $L + r$ at echelon k, $\bar{X}_t$ be an estimate of the mean lead time demand, and s_X be the standard deviation of its estimate. The lead time demand realized from time t is

$$X_t = \sum_{i=1}^{L+r} D_{t+i}\,, \tag{4.1}$$

where t is the beginning of an inventory replenishment period. For the upper echelons, X_t is the order direct lower echelon k - 1 put at the reorder point.

Since the upper echelons do not ship partial orders and the delays are random, the delivery lead time L is not deterministic and bears uncertainties. The total lead time observed by the lower echelon includes the constant delivery shipment time, and the order preparation time which is variable due to insufficient inventory levels of the corresponding immediate upper echelon. Each echelon k estimates the lead time $\bar{L}$ by taking the m previous lead times:

$$\bar{L} = \frac{\sum_{i=0}^{m-1} L_{m-i}}{m}\,, \tag{4.2}$$

where m is the moving average period length (i.e., number of deliveries).

To calculate the mean lead time demand $\bar{X}$ from their immediate lower echelon, each echelon first estimates lead time demand by taking the moving average of the previous orders and dividing it by the reorder period in order to calculate the daily demand estimation:

$$\bar{D} = \frac{\sum_{i=0}^{m-1} X_{m-i}}{m} \cdot \frac{1}{r}\,, \tag{4.3}$$

where $\bar{D}$ is the estimated daily demand from the lower echelon and r is the reorder period. It is worth noting that the daily demand estimation by the upper echelon is calculated with the reorder period, although the lower echelon places its orders considering the reorder period and lead time.

$\bar{X}$ is then estimated using the daily demand and lead time moving average forecasts as follows:

$$\bar{X} = \bar{D} \cdot (\bar{L} + r)\,, \tag{4.4}$$

and the standard deviation s_X, which is essential to determine safety stock is estimated as follows:

$$s_X^2 = (\bar{L} + r) \cdot s_D^2 + \bar{D}^2 \cdot s_L^2\,, \tag{4.5}$$

where s_X^2 is calculated with the conditional variance formula. The derivation of this formula can be seen in Appendix A.

Safety stock (SS) level equals to the standard deviation of the lead time demand multiplied by the z-score.

$$SS_k = z_\alpha \cdot s_{X_k}\,, \tag{4.6}$$

where $k = 1,\ 2,\ 3$, z-score is the coefficient of the desired service level $1 - \alpha$ (i.e., safety factor). The z-score is derived from the predetermined service level, and follows standard normal distribution $z \sim \mathcal{N}(0,\ 1)$.

The order-up-to level S is updated using the estimations above at each replenishment period to ensure the inventory level is sufficient to fulfill demand. S is determined to be the sum of average lead time demand and safety stock:

$$S_k = \bar{X}_k + SS_k\,, \tag{4.7}$$

where $k = 1,\ 2,\ 3$.

As we denoted earlier, order quantity is determined to be the difference between order-up-to-level and inventory position:

$$OQ_k = \max\left(S_k - IP_k,\ 0\right), \tag{4.8}$$

where $k = 1, 2, 3$.

The OEM updates its produce-up-to level S with the estimations of demand and return. Return flow is a stochastic process and the estimated mean return in a reorder period $\bar{R}$ and the standard deviation s_R are estimated with available information. Daily demand is estimated with the same procedures as the lower echelons. The safety stock is calculated by using $Var(X) + Var(R) + 2 \cdot Cov(X, R)$:

$$SS_4 = z \cdot \sqrt{s_{X_4}^2 + s_{R_4}^2 + Cov(X_4, R)}\,, \tag{4.9}$$

where s_{X_4} is derived from the estimation of the standard deviation of the daily demand assuming the daily demand is independent as follows:

$$s_{X_4} = s_{D_4} \cdot \sqrt{(L_p + r)}\,, \tag{4.10}$$

where L_p is the constant production lead time.

Then the OEM's produce-up-to level S is updated with the estimations of demand and return, and the safety stock:

$$S_4 = \bar{X}_4 - \bar{R} + SS_4\,, \tag{4.11}$$

where S_4 refers to the produce-up-to level of new products, as all the returned items in the recoverable inventory are remanufactured without a capacity constraint.

The OEM's new production quantity PQ is limited by the production capacity constraint but can be determined with an increment of one:

$$PQ = \min\left(\max\left(S\text{-}IP,\, 0\right),\, C\right), \tag{4.12}$$

where C is the fixed production capacity.

4.3. Return Estimation

Closed-loop supply chains face uncertainties both from the demand and return processes. In the previous section, we considered the demand estimation. In the following section, we propose three methods for estimating the return quantity. Firstly, the OEM estimates the return flow with the moving average method, as it does with the demand process. This method disregards additional information on the trends, remaining service life, or the number of products in use at a time, and smooths out the fluctuations. Hence, we propose a second method where the OEM utilizes the orbit size, expected service life, and return probability information in the return estimation process. Finally, we evaluate the impact of advanced information on product returns, where the OEM has prior knowledge on upcoming returns.

4.3.1. Return Estimation with Moving Average Method

The OEM estimates returns with the moving average method, using the same period length parameter m as demand estimation. Produce-up-to level S is updated with the moving average estimation $\bar{R}$ and estimated standard deviation s_R. Return estimation and its variance with the moving average is calculated as follows:

$$\bar{R} = \frac{\sum_{i=0}^{m} R_{m-i}}{m}, \tag{4.13}$$

$$s_R^2 = \frac{\sum_{i=0}^{m} (R_{m-i} - \bar{R})^2}{m-1}, \tag{4.14}$$

where R_i is the return quantity at the reorder point i, and m is the moving average period length parameter. In the model, demand and return average is estimated with the same value of m.

4.3.2. Return Estimation with Orbit Size Information

The OEM utilizes the orbit size, return probability, and the product's expected service life information in this return estimation method. Here, OEM (i.e., echelon $k = 4$) is assumed to observe the exact number of products in use, and each product is used for an independent exponential time with rate γ. Therefore, the return estimation is calculated as follows:

$$\bar{R} = OS_t \cdot \gamma \cdot p \cdot r, \tag{4.15}$$

$$s_R{}^2 = OS_t \cdot \gamma \cdot p \cdot r\,, \tag{4.16}$$

where OS_t is the orbit size at time t, $\gamma \cdot OS_t$ is the failure rate of the Markov process, p is the probability of being returned to the OEM instead of being disposed of, and r is the reorder point. The return estimation is the theoretical upper bound that enables us to observe the effect of OS_t.

Safety stock level is determined with this return estimation method as:

$$SS = z \cdot \sqrt{s_X^2 + s_R^2}\,, \tag{4.17}$$

and $Cov(X, R) = 0$.

4.3.3. Advanced Return Information

In this study, we also analyze the impact of the advanced return information (ARI), where OEM knows the exact quantity of returns. The return information is provided by the customer after the purchase of the product. Advanced return information can be considered for various business models such as lease contracts, warranty returns, or trade-in programs where the customers bring their old products at the end of the lease term.

The OEM's safety stock calculation with this return estimation method is adjusted as:

$$SS = z_\alpha \cdot s_X\,, \tag{4.18}$$

where only the order variability is included since the variance of return is 0.

Advanced return information is utilized by the OEM to make production decisions. We analyze whether the perfect return information has a diminishing impact on the order variability, and compare the output with the return estimation methods, with moving average and orbit size information.

4.4. Alternative Order-Shipment Policies

In this section, we discuss three alternative replenishment policies: base policy, no safety stock policy and batch shipment policy. As described earlier, base policy ships the orders in one batch when the complete order quantity is available in the inventory. No safety stock policy orders the estimated demand and omits safety stock. In the batch shipment policy, we analyze the supply chain where the upper echelon ships all available products in stock at each shipment until the order is fulfilled.

4.4.1. Base Policy

In this policy, the order is delivered in a single shipment, which might lead to a longer period of stock-out for lower echelons. When the order quantity of the lower echelon is greater than the net stock, the wholesaler, distributor, and OEM withhold the order until the complete order quantity is available. The order delivery process consists of order preparation and shipment. The shipment takes a constant lead time, whereas the order preparation process could be prolonged due to the lack of available stock. Since the order delivery process starts when the order is placed, the delivery lead time L is at least as much as the shipment lead time.

4.4.2. No Safety Stock Policy

With the no safety stock policy, we analyze the replenishment process where the orders are determined only with the demand estimation, and whether the orders placed by the lower echelon without considering the safety stock help reduce the delivery lead times.

In this policy, the order-up-to level S without the safety stock is calculated with the demand estimation for echelons $k = 1, 2, 3$ (i.e., retailer, wholesaler, and distributor) as follows:

$$S_k = \bar{X} \, , \tag{4.19}$$

where $\bar{X}$ is the estimation of lead time demand.

The OEM (i.e., $k = 4$) calculates its produce-up-to level S as follows:

$$S_4 = \bar{X} - \bar{R}\,, \tag{4.20}$$

where $\bar{R}$ is the estimation of returns.

4.4.3. Batch Shipment Policy

In previous scenarios the shipment starts when the complete order quantity is available in the stock. The entire order is delivered in a single shipment. This procedure has a potential of increasing the order preparation time and leading to longer periods of stock-outs for lower echelons. Since the echelons update their order-up-to level with their inventory position, on-order inventory in preparation may distort the ordering decisions even with a net stock of zero, especially when the delivery lead-time exceeds the reorder period interval. We study this phenomenon in more detail in Numerical Analysis.

To overcome the unnecessarily long periods of stock-outs, we consider the shipment policy with partial deliveries. In this policy, the upper echelon ships all available stock is shipped even if the amount is less then the order quantity. Any remaining order is shipped at successive shipment times subject to stock availability. The most important advantage of this policy is the sustained flow of products through the supply chain.

4.5. Performance Metrics

In this study, we focus on the increase in order variability across the tiers of the closed-loop supply chain and how demand amplification affects inventory levels and manufacturing output when return flows are taken into account. Fluctuations in the demand, return flow, and lead time result in imprecise forecasts, and understanding their impact can provide insights into mitigating uncertainties inherent to supply chains. We evaluate the processes with five metrics: bullwhip effect ratio, net stock amplification, average fill rate, and order cycle time.

4.5.1. Bullwhip Effect Ratio

The bullwhip effect (BWE) represents demand amplification as orders move up the supply chain. The orders are placed in upper echelons at the beginning of the reorder period r with order-up-to policy $(r,\ S)$. Uncertainty in the customer demand transferred across the echelons with additional forecasting variability. To quantify this phenomenon, the bullwhip effect is defined as the ratio of variance of the order placed in echelon k to variance of customer demand:

$$BWE_k = \frac{\sigma^2_{O_k}}{\sigma^2_D}\ , \tag{4.21}$$

where $\sigma^2_{O_k}$ is the variance of order at echelon $k = 1,\ 2,\ 3,\ 4$ and σ^2_D is the variance of customer demand seen at the retailer level.

4.5.2. Net Stock Amplification

We quantify the impact of the inventory replenishment process on the net stock (i.e., on-hand inventory) using the Net Stock Amplification (NSA) measure. NSA is the ratio of net stock variance to the variance of customer demand.

$$NSA_k = \frac{\sigma^2_{NS_k}}{\sigma^2_D}\ , \tag{4.22}$$

where $\sigma^2_{NS_k}$ is the variance of the net stock at echelon $k = 1,\ 2,\ 3,\ 4$ and σ^2_D is the variance of customer demand seen at the retailer level.

BWE is the measure of increasing variability upstream, and NSA is related to the echelons' desired service level performance [55]. Dampening the BWE results in reduced costs for the upper echelons at the expense of order fill rate [56]. Hence, NSA and BWE have compromising objectives, the former with increasing the service level downstream, and the latter with reducing costs upstream.

4.5.3. Average Fill Rate

The Fill Rate (FR) is the portion of the order echelons can fulfill immediately with their on-hand inventory without lost sales or back orders. Fill Rate is calculated as the ratio of fulfilled demand to total demand at order arrival time t, and the Average Fill Rate is simply the average of FR recorded for each reorder period:

$$FR_{k,t} = \frac{min(X_{k,t}, NS_k)]}{X_{k,t}} \cdot 100\,, \tag{4.23}$$

$$AFR_k = \frac{\sum_t FR_{k,t}}{r_{eff}}\,,$$

where $k = 1, 2, 3, 4$, and NS is the net stock. AFR is calculated with r_{eff}, the number of reorder periods with positive order quantity, since the FR is not relevant in the periods with no order.

AFR is a measure of customer responsiveness and strongly correlated with the service level. Higher AFR indicates efficient and quick shipment, minimized lead time, lost sales, and back orders.

4.5.4. Order Cycle Time

Order cycle time or order lead time is the time between the entry of the order and the delivery of the finished goods. Long delivery lead time can aggravate the bullwhip effect by causing fluctuations in the order rate [57]. A shorter order cycle time also leads to competitive advantage as it directly determines customer service [58].

$$T_{k,k-1} = \frac{\sum \text{Delivery Date} - \text{Order Date}}{n}\,, \tag{4.24}$$

where order cycle time T is calculated for $k = 2, 3, 4$, and n is the number of shipments in the simulation run.

4.6. Model Verification and Validation

Simulation models are efficient tools to solve real-life problems and can provide insights into the underlying processes in complex systems. Since the analyses derived from the simulation results are used for decision-making purposes, quantifying the accuracy of the real-life representation and confidence in predictions is an integral step to confirm the credibility of the model. Model verification and validation addresses the assessment of the computer implementation and consistency with the intended application [59].

In order to verify our simulation model, we generate outputs for various configurations and compare the results with expected outcomes. Firstly, we remove the random variables to evaluate whether the model is behaving appropriately in a deterministic setting. After confirming the representation of the entities, we introduce the random variables related to the statistical distributions.

We then conduct extreme condition tests to assess the plausibility of the model structure and outputs. The model behaves as expected with conditions such as no demand, no production, and demand greater than supply. The variability in customer demand and product lifetime adequately fits the statistical distribution of the model parameters. We also verify the inventory replenishment process by individually checking the delivery processes and changes in the inventory levels at each echelon.

As we consider a stylized multi-echelon supply chain model with return flows to observe the impact of return information on the bullwhip effect, we cannot perform validation with real-life data. Instead, we conducted a sensitivity analysis to assess the model's validity. To assess how the output changes in relation to the fluctuations in the parameters, we used a primary experimental design. As an example of the sensitivity analysis, Table 4.1 and Figure 4.2 summarizes the change in sales in relation to customer demand.

Table 4.1. Change in the average sales in relation to the average customer demand.

Average Demand	Change in Demand	Average Sales	Change in Sales
75	-	67.95	-
60	15	53.51	14.44
45	30	39.61	28.34
30	45	25.59	42.36
15	60	13.25	54.70

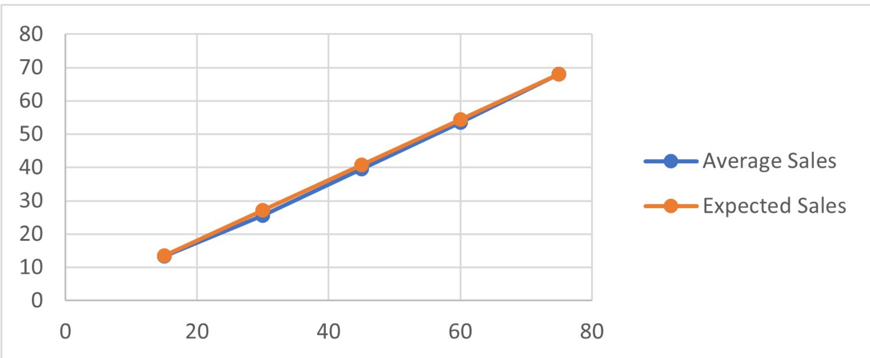


Figure 4.2. Actual and expected change in sales in relation to the demand.

As the return flow increases, capacity utilization is expected to decrease against the remanufacturing proportionally. Figure 4.3 demonstrates the change in capacity utilization with increasing return probabilities in reference to the forward supply chain. The percent change shows a negative linear correlation to the return flow.

When the return probability is 0.1, the capacity utilization decreases by 10% compared to that of the forward supply chain. When the return probability is 0.9, the capacity utilization decreases by 90%. The decrease in capacity utilization does not imply reduced productivity, but it shows that the production of new items decreases as the product supply shifts to remanufacturing instead.

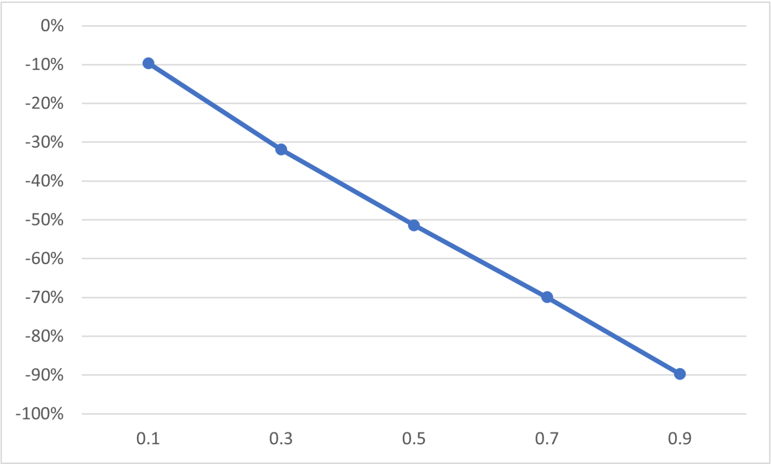


Figure 4.3. Change in capacity utilization from the forward supply chain, $p = (0.1, 0.3, 0.5, 0.7, 0.9)$.

5. NUMERICAL ANALYSIS

After verifying our simulation model, we conduct a numerical analysis to evaluate the impact of parameters of interest on the performance measures, specifically the bullwhip effect. We investigate the factors that contribute to variability reduction in the supply chain. Our main purpose is to determine whether the orbit size and advanced return information provide an improvement for the bullwhip effect in a multi-echelon closed-loop supply with capacitated production.

In this section, we first determine the warm-up period and data collection method, then we study the impact of return probability, reorder period, number of moving average periods, average product lifetime, desired service level, product lifetime variability, and alternative shipment policies. We construct an orthogonal array for the design of experiments and compare the main effect of the factor levels on the performance measures.

We investigate the impact of return estimation methods on the bullwhip effect, so the results are presented as the change in the bullwhip effect from the forward supply chain under the periodic review (r, S) inventory replenishment system without the return flow. We observe the changes in performance metrics with the return flow and different return estimation methods, namely the moving average, orbit size information, and advanced return information. We first experiment with different levels of return probability, reorder period, number of moving average periods, and average product lifetime. Then we present experiments with the desired service level, product lifetime variability, and alternative shipment policies to compare the effect of the return estimation methods.

Traditional forecasting methods such as the moving average are commonly used to estimate demand in forward supply chains as well as return estimation in closed-loop supply chains. However, the correlation between demand and returns is not taken into account in these methods. Constructing more precise return estimation methods could be possible with information about return flow characteristics. We investigate the value of orbit size and advanced return information for more accurate return forecasting.

Information on the quality and quantity of products in use requires significant investment. The orbit size information could be achieved through technologies such as RFID, Ultra-wideband, and GNSS (GPS). Return forecasting with the orbit size information is still an estimation method, retaining the uncertainties in the return flow. The advanced return information method utilizes the exact return information and does not estimate the return flow.

Table 5.1. Model inputs.

Parameter	**Description**
r	Reorder period
λ	Daily demand rate
p	Return probability
γ	Mean product service time
L_m	Manufacturing lead time
L_r	Remanufacturing lead time
L_s	Shipment lead time
DSL	Desired service level
m	Number of moving average periods
PLD	Product lifetime distribution
CV	Coefficient of variation
k	Weibull distribution shape parameter
C	Manufacturing capacity

The complete list of model inputs is given in Table 5.1. Reorder period r is the interval for the inventory replenishment process. Each echelon determines its order-up-to level with its inventory position and demand forecast. Daily demand rate λ

follows Poisson distribution and customer demand arrives at the retailer echelon one by one. Products are returned to the OEM with return probability p. Products are manufactured and remanufactured with lead times L_m and L_r, which are constant in the model. Shipment lead time L_s is also constant and it sets the minimum time required for order delivery, as the total delivery lead time depends on order preparation time as well. DSL represents the desired service level, the rate at which the supply chain echelons aim to meet the demand from their lower echelon. The desired service level is directly used to determine the safety stock. m is the number of moving average periods, the number of historical data points used to forecast demand. m is also a parameter for return forecasting when return flow is estimated with the moving average method. PLD is the statistical distribution of the product lifetime and is set to exponential, log-normal, and Weibull distributions in the model. CV is the coefficient of variation for the log-normal distribution, allowing us to experiment with different reliability specifications. k is the shape parameter for the Weibull distributed product lifetime. C is the manufacturing capacity for the new products and is constant in the model.

5.1. Data Collection Approach

We study the stationary behavior of the supply chain in consideration. To this end, we first determine the warm-up period for our simulation. Then, we adopt the batch means method for data collection. The degree of correlation among batches needs to be inspected to eliminate any bias. We determine the warm-up period, namely the time when the orbit reaches steady state, the batch size that minimizes the correlation, as well as the simulation run time. We set the size of the batches to 2000 time units, and the number of batches to 30, the autocorrelation of the batches is found to have a weak degree, as demonstrated in Figure 5.1.

Schmeiser [60] showed that there is little to no benefit if the number of batches is larger than 30, and the recommended range was between 10 and 30 batches. On the other hand, large batch size is necessary to ensure independence between the batches. In order to ensure independence while maintaining a somewhat smaller variance for the estimator, we set the number of batches to 30. The batch size varies according to the reorder period; as the simulation run time is constant, the batch size is lower when the reorder period is 15 compared to 7.

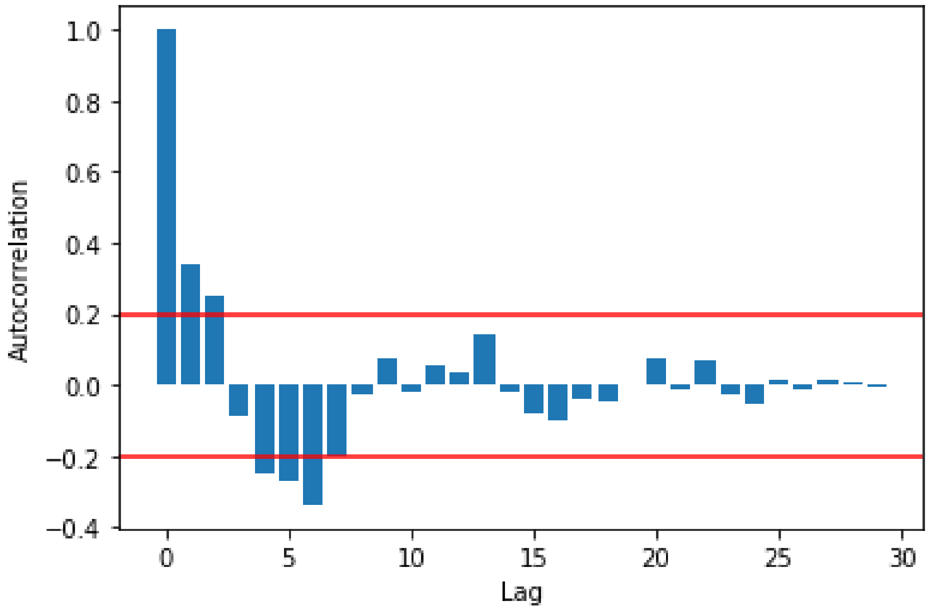


Figure 5.1. Autocorrelation between retailer BWE batch means, $r = 15$, $p = 0.5$, $\gamma = 720$, $m = 30$.

We determine the warm-up period with the randomization test. Yücesan [61] introduced a method based on randomization tests to detect the initialization bias. This method analyzes the null hypothesis that there is no initialization bias. The main advantage of this method is that no assumptions such as normality are required. We first run the simulation for 5000 days with the 15-day reorder period and obtain the output time series for the return flow. We group the data into 30 mutually exclusive batches and obtain batch means. Batches are partitioned into two groups starting with the first batch in the first group and 29 batches in the second group. We compare the grand means of the two groups and check the significance of the difference between the two means. If the null hypothesis is rejected we add one more batch to the first group and repeat the comparison step. The null hypothesis is not rejected at simulation time 1800. We set the warm-up period at 2000 for ease of computation in the simulation model. The batch size is recommended to be larger than or equal to the warm-up period [62], hence, the simulation run time is determined to be 62000 days. The data of the first 2000 days is deleted before calculating the batch means.

5.2. Experimental Design

We experiment with multiple supply chain parameters to inspect their impact and the performance of different return estimation methods. We utilize Taguchi orthogonal arrays for the design of experiments. The parameters and their levels are summarized in Table 5.2.

Table 5.2. Experiment parameter values.

Parameter	**Levels**
Reorder Period	7, 15
Return Probability	0.1, 0.3, 0.5, 0.7, 0.9
Moving Average Periods	15, 30
Average Product Lifetime (days)	360, 1080

Figure 5.2 demonstrates the experimental setting, bullwhip effect in the forward supply chain, and change in bullwhip effect with different return estimation methods at the distributor echelon. We collect the results for each experimental setting, echelon, and performance measure. The return estimation methods, namely the moving average (MA), orbit size information (OS), and advanced return information (ARI), improve the bullwhip effect compared to the forward supply chain thanks to the return flow. We analyze the impact of each parameter and return estimation method in the following sections in more detail. The figures show the average change in the performance measure with the return estimation methods from the forward supply chain. For example, a -20% change with 0.5 return probability for the moving average at any echelon represents a 20% decrease in bullwhip effect from the forward supply chain with no returns to the closed-loop supply chain with 0.5 return probability when the

return flow is estimated with the moving average. The percent change values under the MA, OS, and ARI are calculated as follows:

$$\%change = \frac{BWE_{FSC} - BWE_i}{BWE_{FSC}} \cdot 100\,, \tag{5.1}$$

where i = MA, OS, and ARI.

Exp. #	p	r	m	γ	FSC	MA	OS	ARI
1	0.1	7	15	360	16.24	-48%	-54%	-45%
2	0.1	7	30	1080	11.06	-40%	-33%	-31%
3	0.1	15	15	1080	14.73	-38%	-17%	-23%
4	0.1	15	30	360	7.41	-37%	-43%	-48%
5	0.3	7	15	360	16.24	-50%	-52%	-53%
6	0.3	7	30	360	21.91	-66%	-69%	-72%
7	0.3	15	15	1080	14.73	-34%	-34%	-29%
8	0.3	15	30	1080	6.60	-22%	-22%	-44%
9	0.5	7	15	1080	19.43	-63%	-61%	-62%
10	0.5	7	30	1080	11.06	-50%	-46%	-47%
11	0.5	15	15	360	19.70	-49%	-52%	-50%
12	0.5	15	30	360	7.41	-30%	-35%	-20%
13	0.7	7	15	360	16.24	-63%	-64%	-60%
14	0.7	7	30	1080	11.06	-63%	-61%	-61%
15	0.7	15	15	360	19.70	-63%	-66%	-58%
16	0.7	15	30	1080	6.60	-33%	-51%	-46%
17	0.9	7	15	1080	19.43	-79%	-80%	-78%
18	0.9	7	30	360	21.91	-87%	-87%	-86%
19	0.9	15	15	1080	14.73	-76%	-73%	-72%
20	0.9	15	30	360	7.41	-68%	-68%	-64%

Figure 5.2. Orthogonal experiment design, BWE in the forward supply chain, and change in BWE with the return flow and return estimation method at the distributor echelon.

5.2.1. Impact of Model Parameters

In this section, we further analyze the impact of return probability, reorder period, number of moving average periods, and average product lifetime on the performance metrics at each echelon. We compare the performance of return estimation methods for different experiment settings and investigate whether the orbit size or advanced return information creates an advantage over return estimation with the moving average.

Table 5.3 summarizes the performance metrics investigated.

Table 5.3. Performance metrics.

Performance Metric	**Description**
Bullwhip Effect Ratio (BWE)	Demand amplification
Net Stock Amplification (NSA)	Inventory fluctuation
Average Fill Rate (AFR)	Percentage of orders available in stock
Order Cycle Time (T)	Time between the order date and delivery

5.2.1.1. Return Probability. Customers return their end-of-life products with a return probability set in the model. The higher the return probability, the more the OEM supplies products through remanufacturing. The refurbished products can be sold separately and at reduced prices. However, we assume the remanufactured items are as good as new and the customer demand is not separate for these products.

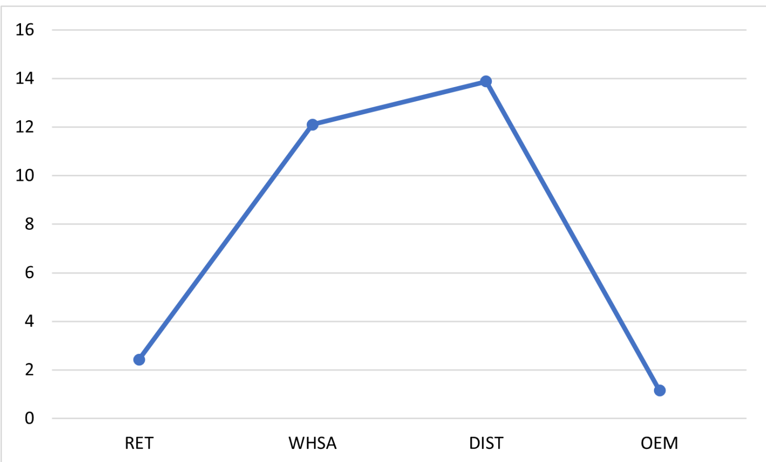


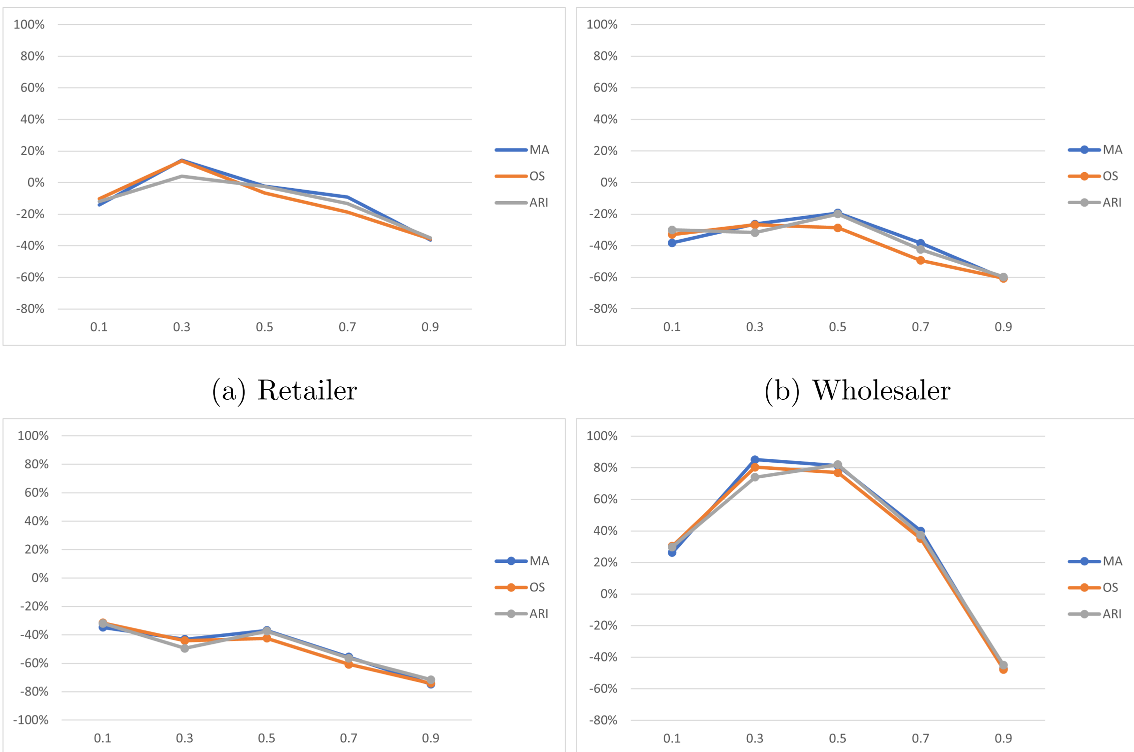
Figure 5.3. Average bullwhip effect at each echelon in the forward supply chain.

Figure 5.3 demonstrates the average bullwhip effect of our experiments in the forward supply chain with no return flow. The bullwhip effect gradually increases upstream as expected, but the manufacturer experiences the lowest order variability due to the limiting effect of the capacity constraint. In the forward supply chain, demand variability is the main source of uncertainty, whereas the return flow adds to the uncertainty in a closed-loop supply chain. We first present the main effect of the return probability levels on the bullwhip effect, net stock amplification, average fill rate, and order cycle time.

The average percent change in the bullwhip effect with the return flow using different return estimation methods for each echelon is demonstrated in Figure 5.4. Compared to the traditional supply chain with only forward flow, in the bullwhip effect decreases with all three return estimation methods at the retailer, wholesaler, and distributor echelons. At the retailer level, the bullwhip effect slightly decreases with the introduction of return flow with a return probability of 0.1. However, the return probability of 0.3 increases the order variability as the increasing uncertainty from the return flow cannot be overcome with the growing product supply from remanufacturing. We also observe the return estimation with advanced return information is more resilient to this change and performs better than the other return estimation methods to stabilize the bullwhip effect.

The bullwhip effect at the retailer echelon goes back to the forward supply chain levels with a 0.5 return probability and keeps decreasing with the increasing return flow. At these levels of return probability, the orbit size information reduces the bullwhip effect more than the moving average and advanced return information. At the wholesaler level, the bullwhip effect is less than the forward supply chain for any value of return probability, with the lowest and highest return flow rates favored. Bullwhip effect at the wholesaler level can be reduced by up to 60%. Orbit size information performs better with higher return probabilities, similar to the results at the retailer level. The distributor observes a decreasing bullwhip effect with an increasing return probability, with a much more prominent change compared to the downstream echelons. The decrease in the bullwhip effect reaches 60% at the distributor level with 0.9 return probability.

The change in the bullwhip effect at the OEM level is noticeably different from the downstream echelons, as the introduction of return flow increases the order variability by more than 80%, except for the maximum rate of return. The production capacity constraint stabilizes the production variability at the OEM level, but the return flow disrupts the steady manufacturing decisions. The uncertainty brought by the return flow cannot be balanced out until the return probability reaches 0.9, where the bullwhip effect is 40% less than the forward supply chain. Since the OEM accepts all returns as remanufacturable, the serviceable inventory is lower than the produce-up-to level by a small margin consistently. At the OEM level, the difference between the return estimation methods is insignificant.



(a) Retailer (b) Wholesaler

(c) Distributor (d) OEM

Figure 5.4. Main effect of the return flow with increasing return probabilities on the average change in BWE from the forward supply chain.

Table 5.4 presents the p-values of the ANOVA test between the forward supply chain and return estimation methods in the closed-loop supply chain. We analyze these results at $\alpha = 0.05$ significance level. The p-values represent the significance of the return flow with the return probability p at each echelon for the bullwhip effect. If the p-value implies significance, we compare the return estimation methods with Tukey's range test. The return flow is significant at the retailer level only with return probability $p = 0.9$, and the pairwise comparison of the moving average, orbit size information, and advanced return information shows that the difference between the return estimation methods is insignificant. For the wholesaler and distributor, the return probabilities 0.7 and 0.9 have a significant impact on the bullwhip effect, but the difference between the return estimation methods is insignificant. At return probability 0.3, the advanced return information is the only return estimation method with a significant difference with the forward supply chain at the wholesaler and distributor echelons. Finally, at the OEM echelon the return probability of 0.9 has a significant impact, but the return estimation methods do not have a significant difference at this echelon as well. We can comment that the orbit and advanced return information does not provide a significant advantage to control the bullwhip effect in the closed-loop supply chain with production capacity. The capacity constraint set a low ceiling for the bullwhip effect, and improvements in return estimation is not the primary direction.

Table 5.4. P-values of ANOVA test for the forward and closed-loop supply chains' bullwhip effect at each echelon.

p	**RET**	**WHSA**	**DIST**	**OEM**
0.1	0.84	0.21	0.26	0.51
0.3	0.93	0.06	0.03	0.06
0.5	0.99	0.39	0.97	0.09
0.7	0.57	0.04	0.01	0.57
0.9	0.00	0.00	0.00	0.00

Figure 5.5 demonstrates the average net stock amplification at each echelon for the forward supply chain. In a capacitated production supply chain, the net stock amplification is highest at the retailer echelon and lowest at the OEM. The wholesaler

and distributor's net stock amplification is similar. In the forward supply chain with production capacity, the net stock amplification generally decreases upstream.

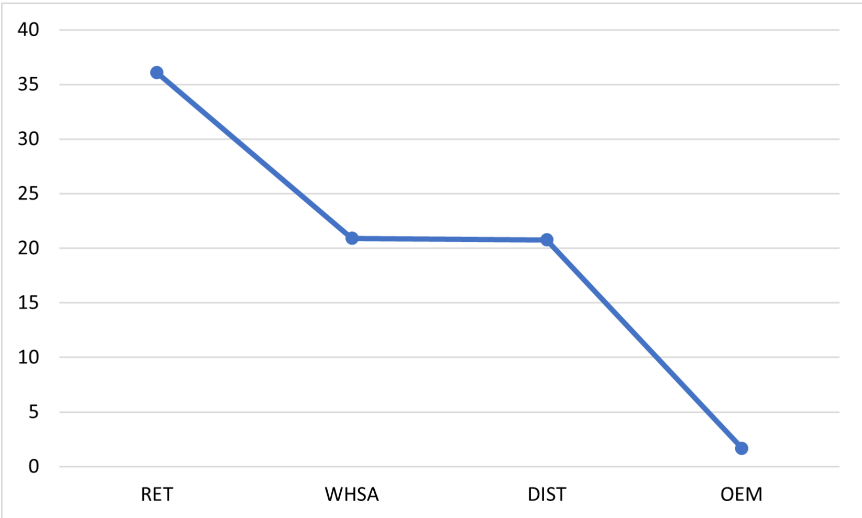


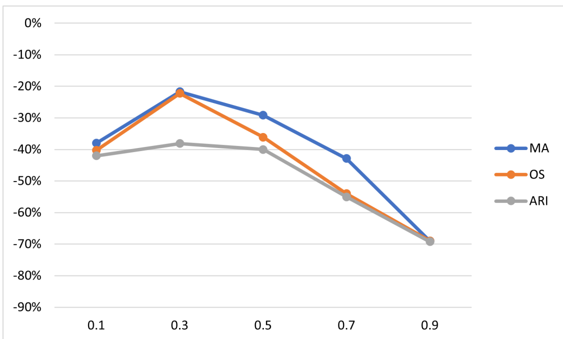
Figure 5.5. Average NSA at each echelon in the forward supply chain.

Figure 5.6 summarizes the main effect of return probability on the change in net stock amplification for each echelon. The retailer, wholesaler, and distributor see a decrease in their net stock variability for all return probability values and return estimation methods. The decrease in net stock amplification is significant particularly with the higher return probabilities.

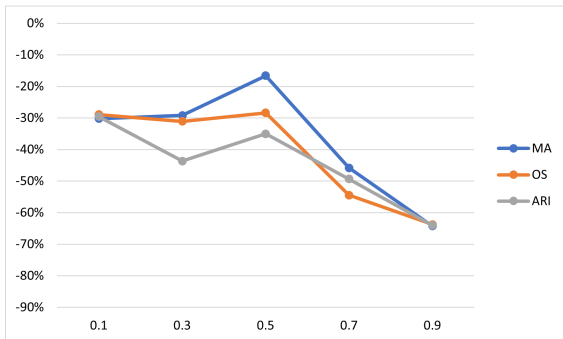
Since the production capacity limits the product flow in the forward supply chain, remanufactured products improves the product supply downstream as the stock outs become less common. Net stock amplification at the OEM drastically increases with the increasing return flow as all return products are remanufactured and placed in the serviceable inventory.

Table 5.5 shows the p-values for the net stock amplification at the echelons. The impact of the return flow is more significant for the net stock amplification compared to the bullwhip effect at the retailer echelon. As for the pairwise comparison of the return estimation methods, the difference is significant between the advanced return estimation and the other return estimation methods at the retailer, wholesaler, and distributor echelons with a return probability of 0.3, whereas the return estimation method does not have a significant impact on the net stock amplification for other return probability values.

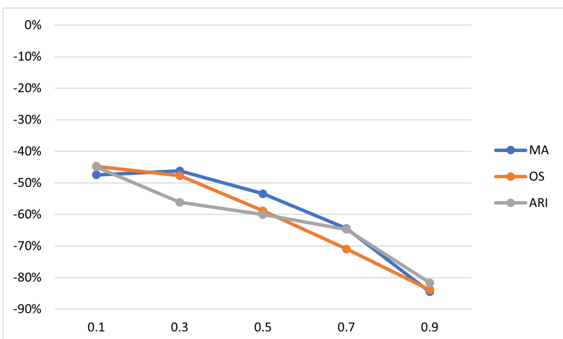
At the OEM level, the return flow has a significant impact on the net stock amplification with return probabilities higher than 0.1. The change in net stock amplification at the OEM echelon is greater than that of the bullwhip effect, since the production variability is limited but the new production constraint, but all returned products are remanufactured and added to the serviceable inventory.



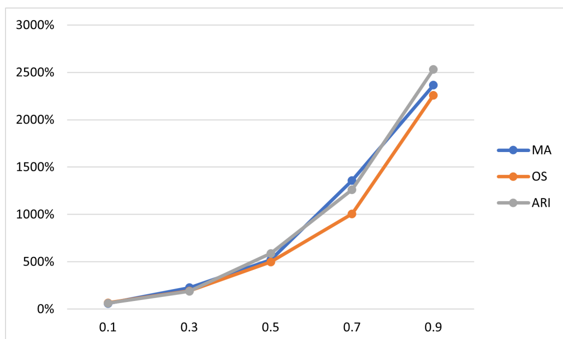
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.6. Main effect of the return flow with increasing return probabilities on the average change in NSA from the forward supply chain.

Table 5.5. P-values of ANOVA test for the forward and closed-loop supply chains' net stock amplification at each echelon.

p	**RET**	**WHSA**	**DIST**	**OEM**
0.1	0.04	0.27	0.14	0.19
0.3	0.09	0.02	0.03	0.04
0.5	0.07	0.23	0.09	0.04
0.7	0.00	0.00	0.02	0.02
0.9	0.00	0.00	0.01	0.00

Figure 5.7 demonstrates the average fill rate in the forward supply chain. The average fill rate decreases upstream since the customer demand arrive one by one at the retailer, but the orders from the lower echelons arrive as lead time demand with safety stock added. The capacitated OEM's fill rate is around 40% without the remanufactured products. The mid-level echelons wholesaler and distributor operate with similar fill rates, but the general trend in this performance measure is decreasing fill rates in the upstream.

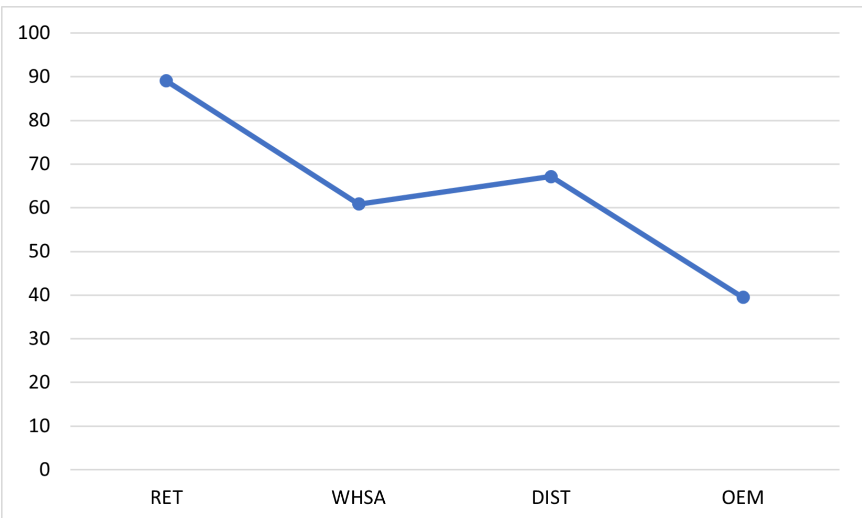
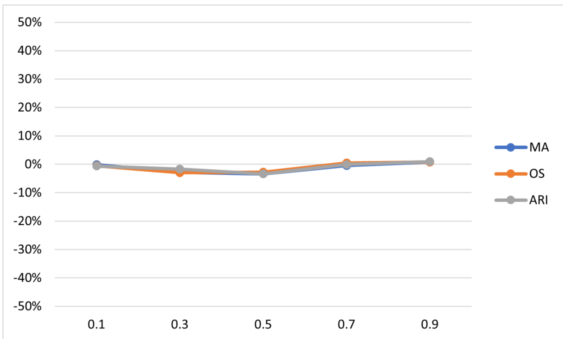
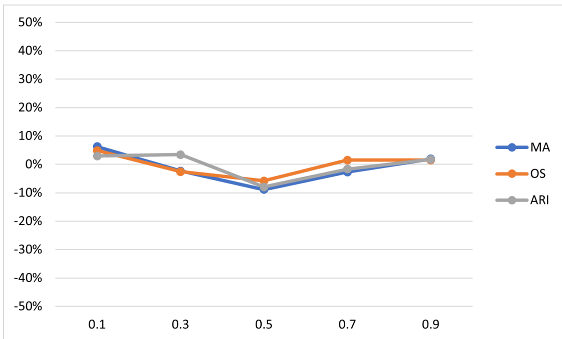


Figure 5.7. Average AFR at each echelon in the forward supply chain.

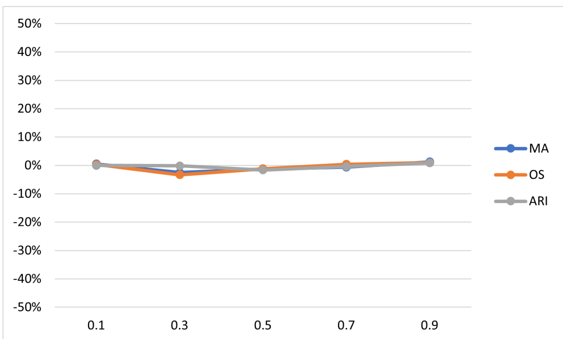
Figure 5.8 demonstrates the change in average fill rate against the return probabilities. The return flow does not have a significant impact on the average fill rate at the retailer, wholesaler, and distributor echelons. The OEM's average fill rate displays a positive linear correlation with the return probability. The production capacity limits the inventory levels, and the stream of remanufactured products improves the OEM's inventory availability. The return flow has a significant impact on the average fill rate of the OEM for all values of the return probability, but the difference between the return estimation methods is insignificant.



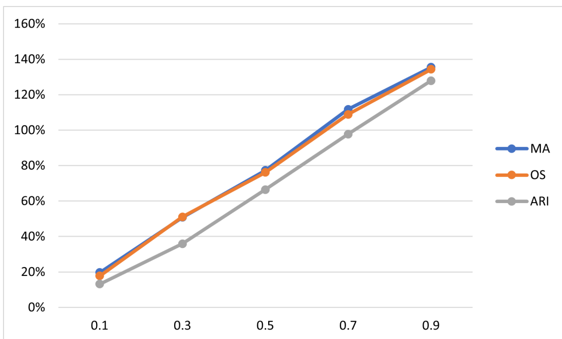
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.8. Main effect of the return flow with increasing return probabilities on the average change in AFR from the forward supply chain.

The average order cycle times in the forward supply chain can be seen in Figure 5.9. The shipment lead time is constant at 3 days, but the stock availability delays the delivery. The delivery lead time is expected to increase upstream but the OEM takes longer to deliver orders to the distributor due to the capacity constraint. The order cycle time reaches up to 18 days on average between the wholesaler and retailer, longer than the highest level of reorder period at 15 days. The capacity constraint is the main driver of these excessive delays in the delivery process.

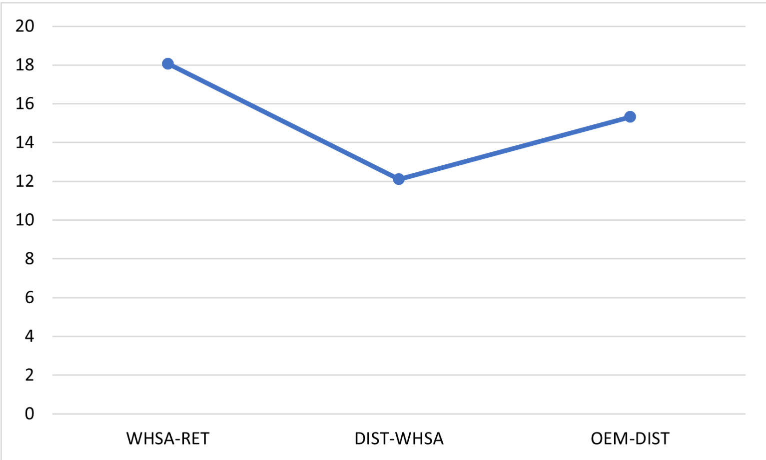
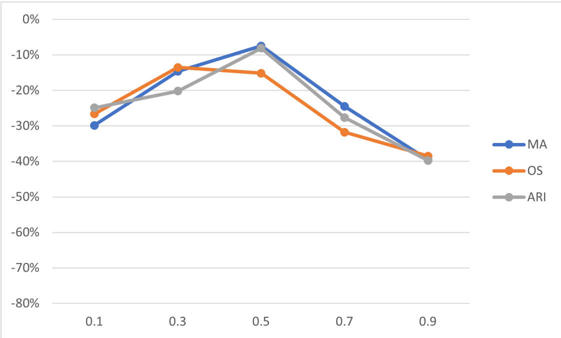


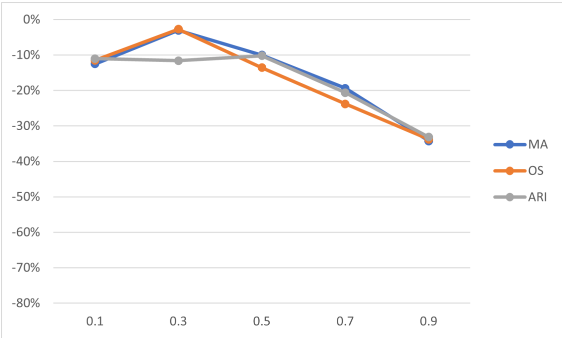
Figure 5.9. Average order cycle time in the forward supply chain.

Figure 5.10 demonstrates the order cycle time between the echelons. The wholesaler delivers retailer orders faster than the forward supply chain scenario for all return probability values, but the moderate improvement at the 0.5 return probability is consistent with the wholesaler's lower fill rate levels. The distributor's delivery time also improves, with the orbit size information reducing lead time more than the other methods due to lower inventory variability and higher fill rates with greater return flow.

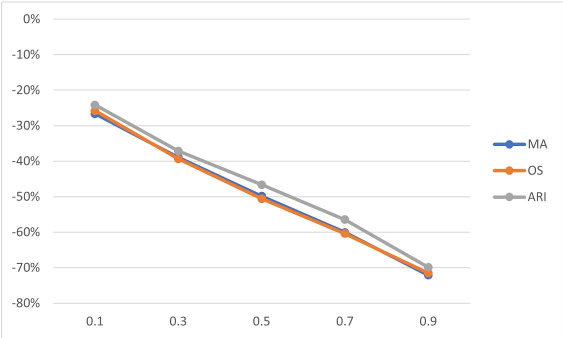
The order delivery from the OEM to the distributor is shorter thanks to the increased product supply from remanufacturing. The return flow has a significant impact on the order cycle time, but the difference between the return estimation methods is insignificant. The order cycle time between the wholesaler and retailer is reduced to an average of 11 days with 0.1 return probability, and to 16 days with 0.5 return probability. The order cycle time between the OEM and distirbutor improves the most, decreasing from 15 days to 11 days with 0.1 return probability, and to 4 days with 0.9 return probability.



(a) Wholesaler-Retailer



(b) Distributor-Wholesaler

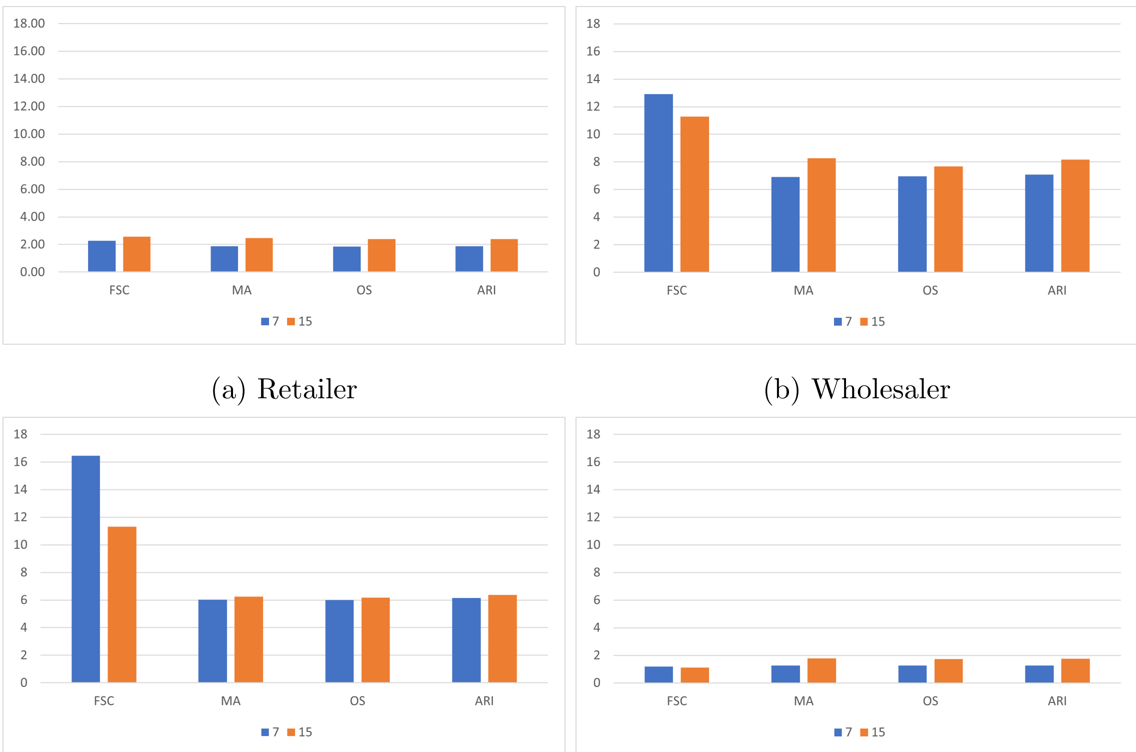


(c) OEM-Distributor

Figure 5.10. Main effect of the return flow with increasing return probabilities on the average change in order cycle time from the forward supply chain.

5.2.1.2. Reorder Period. In this section, we analyze the impact of the reorder period. The supply chain echelons make inventory replenishment decisions every 7 or 15 days. The production capacity is set to 8 units for 7-day, and 16 units for 15-day reorder period. There is a significant difference between the reorder period parameters in terms of the change in performance measures from the forward supply chain to the closed-loop supply chain. Although the reorder period of 7 days resulted in a higher bullwhip effect for the forward supply chain at the distributor and wholesaler echelons, the return flow improves the order variability more than it does with 15-day reorder period.

The bullwhip effect values at each echelon can be seen in Figure 5.11 for the forward and closed-loop supply chain. The 15-day reorder period results in higher order variability for both forward and closed-loop supply chains at the retailer and OEM echelons. The 7-day reorder period benefits from the return flow more than the 15-day reorder period for all echelons. Although the 7-day reorder period was expected to have a lower bullwhip effect due to its flexibility compared to the longer reorder periods in the forward supply chain, the capacity constraint seems to limit the product supply more in the 7-day period. We set the capacity constraint close to the average periodic demand, and the higher production levels handle the order variance better despite the infrequent production. With the return flow and increased product supply from remanufacturing, the limitation of the capacity constraint is balanced out, and the 7-day reorder period results in less order variability as the echelons can respond faster to the changes in the ordering process.

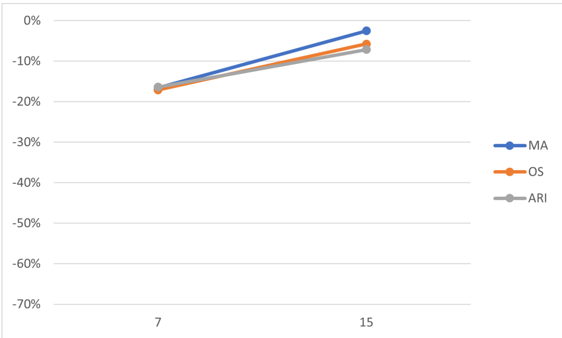


(a) Retailer (b) Wholesaler

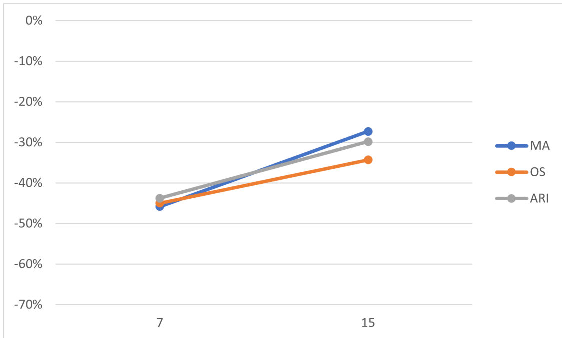
(c) Distributor (d) OEM

Figure 5.11. BWE in the forward supply chain and CLSC with different return estimation methods for reorder periods of 7 and 15 days.

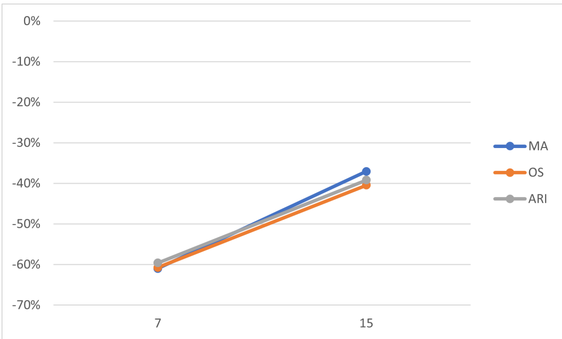
Figure 5.12 demonstrates the main effect of the reorder period on the average change of the bullwhip effect by closing the loop in the supply chain. For the retailer, wholesaler, and distributor echelons, the bullwhip effect sees a higher improvement with the 7-day reorder period compared to the 15-day period. For the OEM, the bullwhip effect increases with the return flow, but the magnitude is lower with the 7-day reorder period. We do not observe a significant difference between the return estimation methods with the 7-day reorder period.



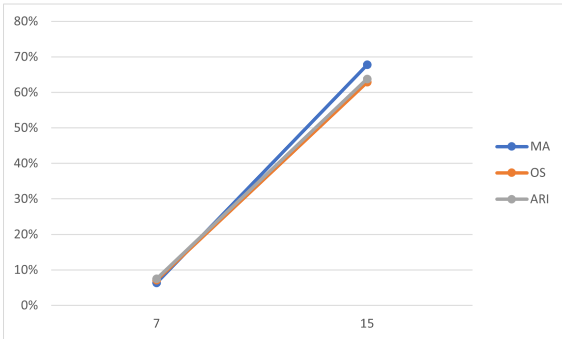
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.12. Main effect of the reorder point on the average change in BWE from the forward supply chain.

Since these values compare the bullwhip effect for the levels of the reorder period, the impact of the return probability and other parameters is less visible. In the forward supply chain, the difference between the reorder period levels is significant at the wholesaler and distributor levels, but the difference fades with the return flow. Table 5.6 demonstrates the p-values of the difference between the reorder period levels.

Table 5.6. P-values of the reorder period levels for the bullwhip effect with the forward supply chain and CLSC.

Echelons	**FSC**	**MA**	**OS**	**ARI**
RET	0.78	0.65	0.67	0.71
WHSA	0.09	0.22	0.57	0.39
DIST	0.04	0.74	0.75	0.74
OEM	0.87	0.81	0.78	0.89

Table 5.7 and Table 5.8 demonstrate the p-values of the difference between the forward supply chain and return estimation methods for reorder periods 7 and 15 respectively. The difference between the forward and closed-loop supply chain is insignificant at the OEM echelon with 7-day reorder period. The return flow has a significant impact on the wholesaler and distributor echelons, whereas the difference between the return estimation methods is insignificant for all echelons.

Table 5.7. P-values for the bullwhip effect, $r = 7$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
RET	0.09	0.07	0.09	0.99	0.99	0.99
WHSA	0.00	0.00	0.00	0.99	0.99	0.99
DIST	0.00	0.00	0.00	1.00	0.99	0.99
OEM	0.97	0.96	0.96	1.00	1.00	1.00

The return flow has a significant impact on the bullwhip effect at the OEM echelon with 15-day reorder period at the OEM echelon along with the distributor and wholesaler. Although the bullwhip effect is reduced more at the wholesaler and distributor echelons with the return flow for 7-day reorder period, the impact is the opposite for the OEM where the bullwhip effect increases more due to the return flow with 15-day reorder period. The return flow has a direct impact on the production decision unlike the order decisions of the downstream echelons, hence the higher and infrequent returns have a greater impact on the bullwhip effect at the OEM echelon.

Table 5.8. P-values for the bullwhip effect, $r = 15$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
RET	0.98	0.95	0.94	0.99	0.99	0.99
WHSA	0.02	0.01	0.02	0.98	0.99	0.99
DIST	0.04	0.03	0.04	1.00	0.99	0.99
OEM	0.03	0.02	0.02	1.00	1.00	1.00

Figure 5.13 demonstrates the net stock amplification in the forward supply chain for reorder periods 7 and 15. At the OEM level, the difference between the levels of the reorder period is insignificant in terms of net stock amplification. However, net stock amplification is higher with 7-day reorder period due to the impact of production constraint as mentioned earlier. The capacity constraint is more restrictive in shorter reorder period, hence the product flow is more limited.

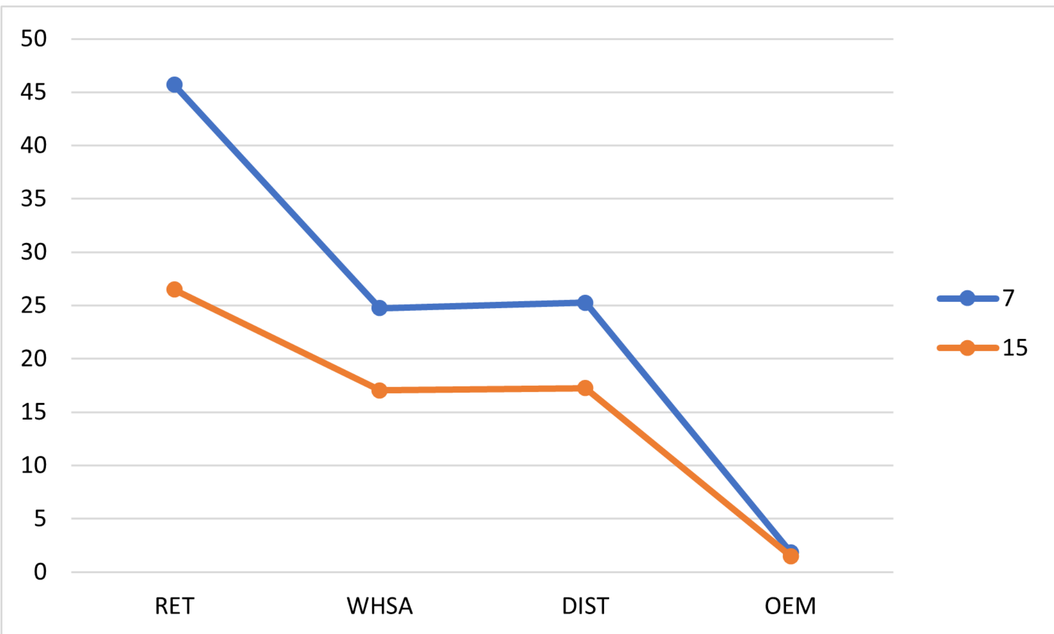
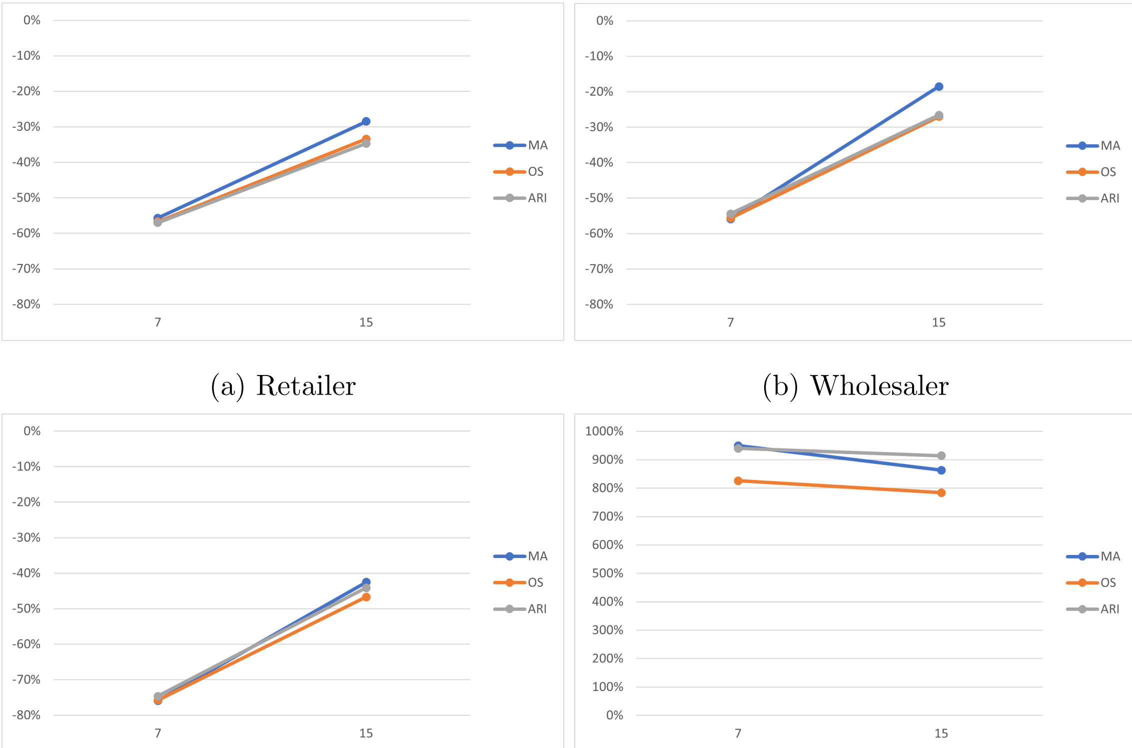


Figure 5.13. Average NSA at each echelon in the forward supply chain.



(a) Retailer (b) Wholesaler

(c) Distributor (d) OEM

Figure 5.14. Main effect of the reorder period on the average change in NSA from the forward supply chain.

Figure 5.14 demonstrates the change in net stock amplification. Similar to the changes observed in the bullwhip effect, the net stock amplification decreases more with the 7-day reorder period. The net stock amplification is higher with the 7-day reorder period than the 15-day period for the forward supply chain. Therefore, we can comment that the impact of the return flow is similar for the net stock amplification for the 7-day reorder period as the bullwhip effect. Return estimation with the orbit size and advanced return information benefits the retailer, wholesaler, and distributor with the 7-day reorder period.

The OEM is also the only echelon to experience an increase in the net stock amplification with the return flow, as the capacity constraint limits the production variability in the forward supply chain. Although the difference between the return estimation methods seem significant at the OEM echelon in this graph, the difference is actually marginal but it is exaggerated due to the low denominator that is the net stock amplification in the forward supply chain. The impact of the return flow is significant, but the return estimation method is not at the OEM echelon.

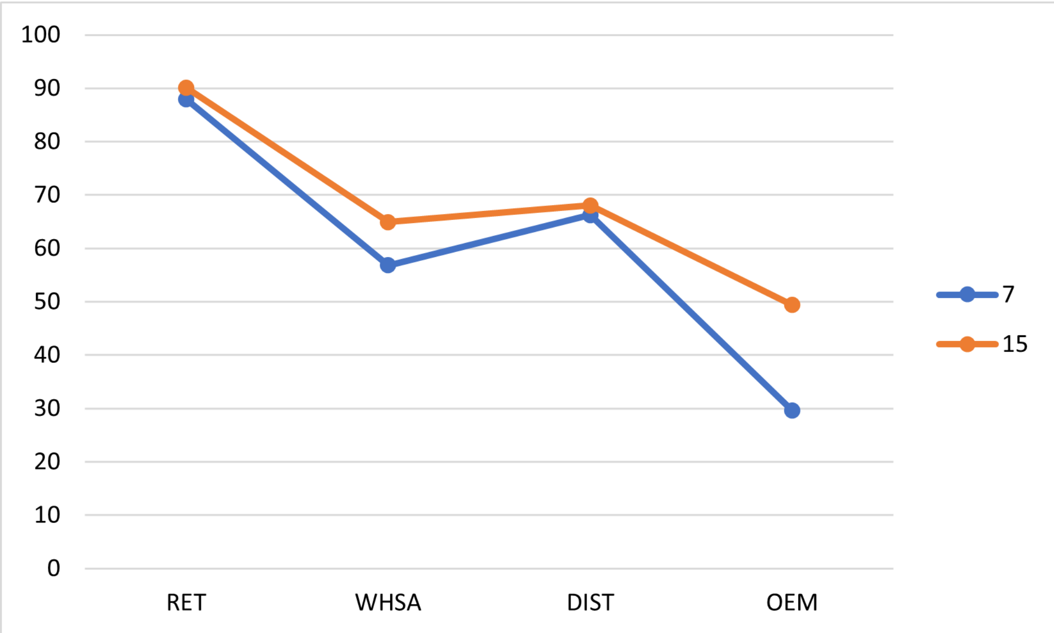
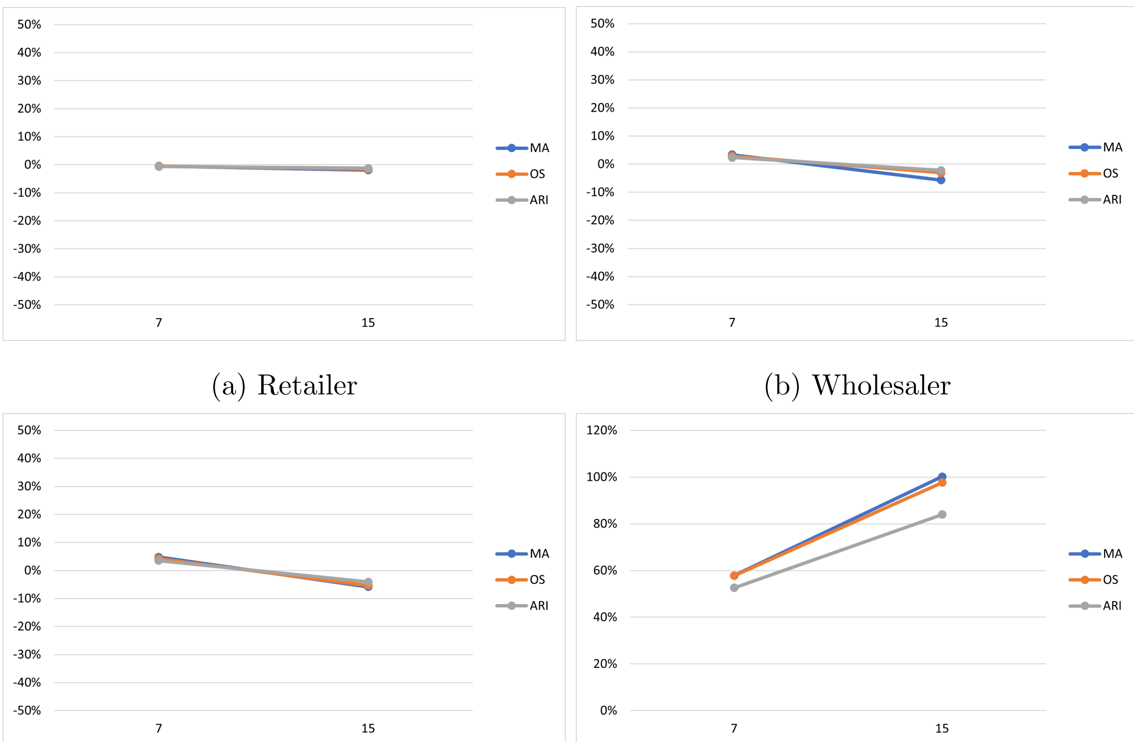


Figure 5.15. Average AFR at each echelon in the forward supply chain.

Figure 5.15 demonstrates the average fill rate for the forward supply chain. The average fill rate is higher with the 15-day reorder period, but the difference is insignificant for the retailer and distributor echelons. The reorder period has a significant impact especially on the OEM due to the capacity constraint. The greater net stock availability with 7-day reorder period is reflected on the average fill rate.

The wholesaler and distributor take longer to deliver the orders to their downstream echelons in the forward supply chain due to the limited product supply. Therefore, their downstream echelons start waiting for the back orders while lowering their order-up-to levels. This behaviour in turn decreases the difference between the orders they receive from downstream and their available inventory, increasing their fill rate. When the return flow is introduced to the supply chain, the product flow increases, but its impact on the fill rate is marginal. The downstream echelons carry smaller a difference between their inventory position and on-hand inventory, so their orders are closer to the estimated demand. The increased product supply with the return flow is balanced out with higher order quantity.

The OEM's fill rate improves for both levels of the reorder period, but the change is more prominent for the 15-day period. Although the increase is higher, the average fill rate for the 7-day reorder period is still higher than the 15-day period. The fill rate of the OEM in the forward supply chain is very low, less than 30% whereas the 7-day period results in a 50% fill rate, so the return flow improves the fill rate drastically. The difference between the return estimation methods is insignificant despite the margins in Figure 5.16.



(a) Retailer

(b) Wholesaler

(c) Distributor

(d) OEM

Figure 5.16. Main effect of the reorder point on the average change in AFR from the forward supply chain.

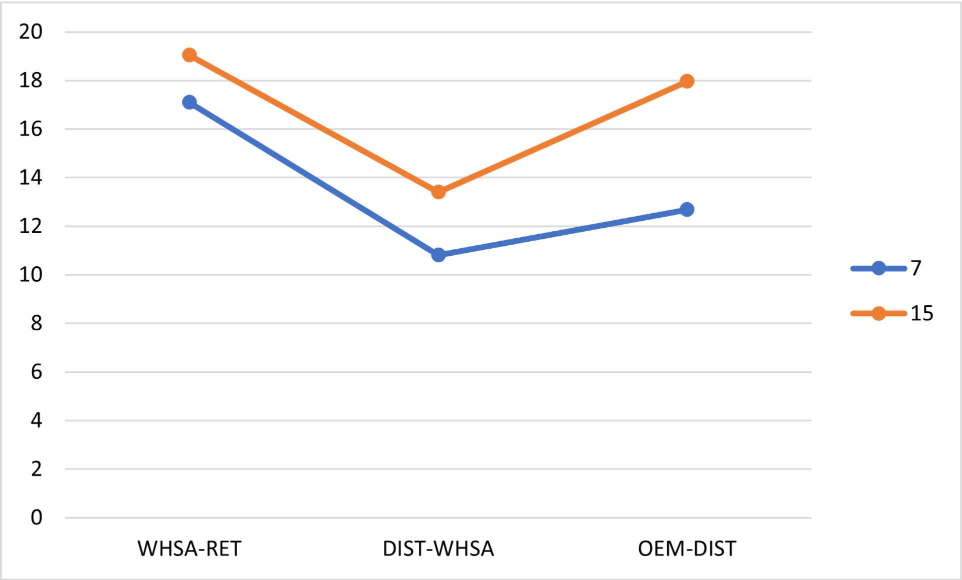
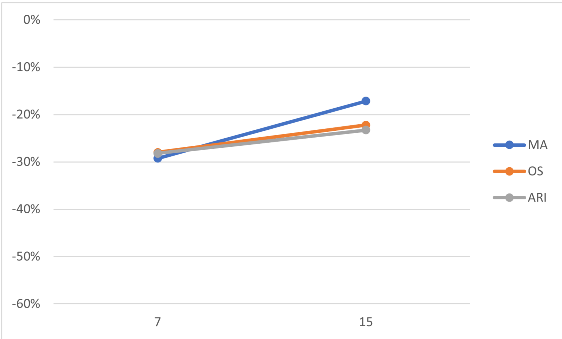


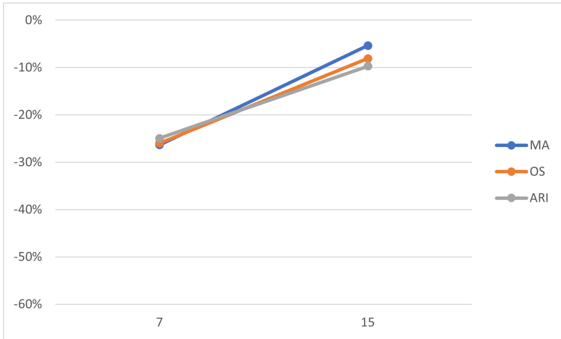
Figure 5.17. Average order cycle time at each echelon in the forward supply chain.

Figure 5.17 shows the order cycle times in the forward supply chain. The delivery lead time is shorter with the 7-day reorder period, but it is important to compare the ratio of the delivery time to reorder period. The order delivery takes up to 19 days for the 15-day reorder period from the wholesaler to retailer. The shipment lead time is 3 days and constant, so the order preparation takes 16 days on average, one day longer than the reorder period. However, the order preparation takes 14 days with the 7-day reorder period which suggests the orders take 2 reorder periods to be prepared. Since the 7-day reorder period leads to higher net stock amplification and lower average fill rate, the delivery lead time is longer.

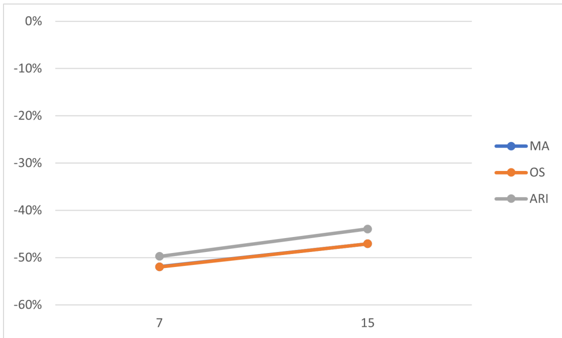
Finally, Figure 5.18 demonstrates the change in order cycle times between the echelons with the return flow. The delivery lead time improves for all echelons with the return flow. Although the difference between the return estimation methods is insignificant, all downstream echelons of the closed-loop supply chain benefit from the return flow. The improvement is much higher for the delivery process between the OEM and distributor as the return flow improves the fill rate significantly at the upstream echelon.



(a) Wholesaler-Retailer



(b) Distributor-Wholesaler



(c) OEM-Distributor

Figure 5.18. Main effect of the reorder period on the average change in order cycle time from the forward supply chain.

5.2.1.3. Number of Moving Average Periods. In this section, we analyze the impact of the number of moving average periods. The demand is always estimated with the moving average of the historical orders, so the number of moving periods is relevant for the forward supply chain and all return estimation methods. However, the impact of this parameter is two-fold for return estimation with the moving average as both demand and return are estimated with the same value. We experiment with 15 and 30 moving average periods.

Figure 5.19 demonstrates the average bullwhip effect in a forward supply chain for 15 and 30 moving average periods. Averaging 30 periods results in less bullwhip effect for all echelons since the order variability is smoothed out. The bullwhip effect is reduced significantly at the distributor echelon. We get similar results for the wholesaler and retailer, although the difference is much smaller for the latter. The number of moving average periods does not have a significant impact on the bullwhip effect in the forward supply chain at the OEM echelon.

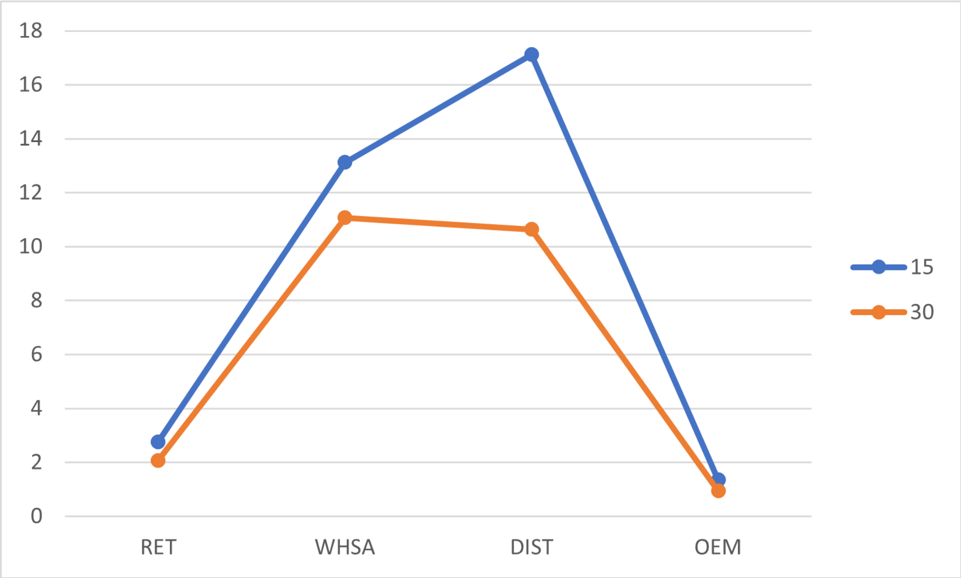
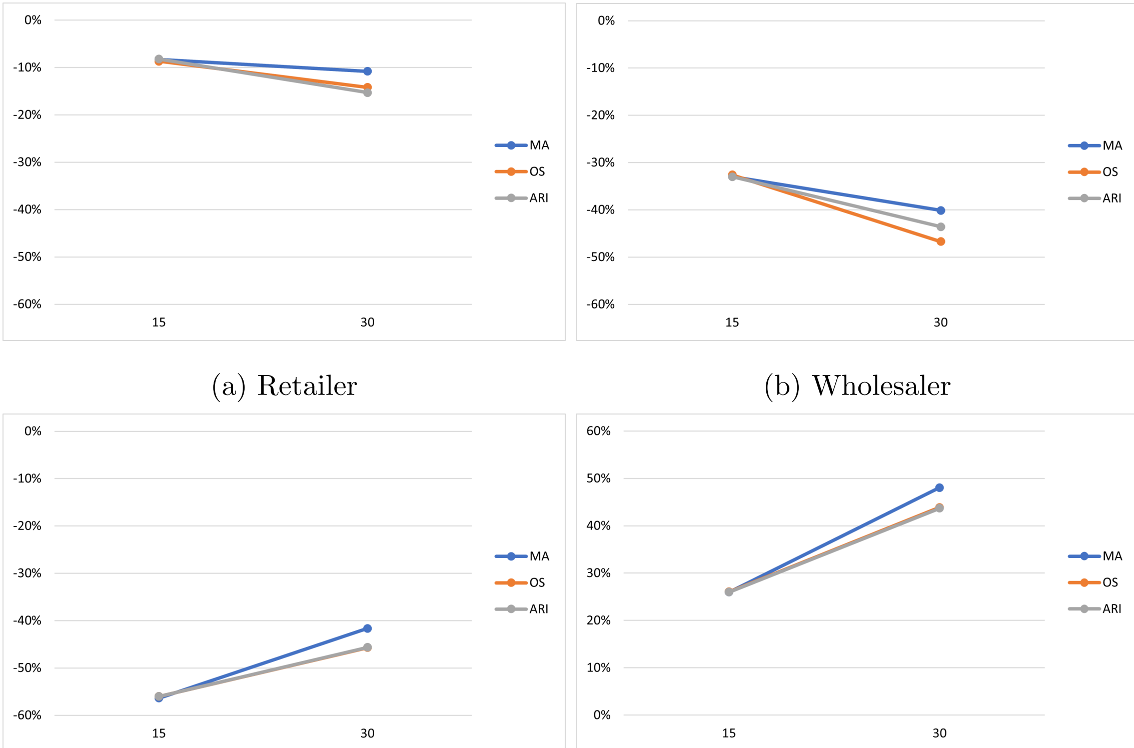


Figure 5.19. Main effect of the number of moving average periods on BWE in the forward supply chain.

Figure 5.20 demonstrates the change in the bullwhip effect for the moving average parameter. At the retailer level, return flow reduces the bullwhip effect for both levels of the moving average periods, but the orbit size and advanced return information methods reduce the bullwhip effect more than the moving average with 30 periods.

At the distributor level, using 15 periods for the moving average benefits more from the return flow, as the distributor was bearing much higher order variability in the forward supply chain. The OEM's order variability increases more with 30 periods, but the change is exaggerated due to lower bullwhip at the OEM in this scenario. Although the change is higher, the bullwhip effect is still lower with 30 periods than with 15 periods at the OEM level.



(a) Retailer

(b) Wholesaler

(c) Distributor

(d) OEM

Figure 5.20. Main effect of the number of moving average periods on the average change in BWE from the forward supply chain.

Table 5.9 demonstrates the p-values of the difference in the bullwhip effect between the forward supply chain and the return estimation methods when the number of moving average periods is 15. In this scenario, the difference between the return estimation periods is insignificant for all echelons at significance level $\alpha = 0.5$, but the impact of the return flow is significant for the wholesaler and distributor echelons. The downstream echelon retailer and the capacity-constrained OEM are not affected significantly by the return flow. Although the higher return probabilities have a significant impact on the bullwhip effect at these echelons, the effect is averaged out when we examine the bullwhip effect for the number of moving average periods. Therefore, when the return probability levels have equal weight, the impact of the return flow is insignificant at the retailer and OEM echelons.

Table 5.9. P-values for the bullwhip effect, $m = 15$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
RET	0.86	0.84	0.87	0.99	0.99	0.99
WHSA	0.00	0.00	0.00	0.99	0.98	0.98
DIST	0.00	0.00	0.00	1.00	0.96	0.98
OEM	0.57	0.57	0.53	1.00	1.00	1.00

When the number of moving average periods is 30, the significance results are similar to that of the 15-period moving average, but the p-values of the difference between the forward supply chain and the CLSC are smaller for the retailer and OEM, as seen in Table 5.10. Therefore, we can comment that the return flow has a greater impact on these echelons when a longer forecasting horizon is used.

Table 5.10. P-values for the bullwhip effect, $m = 30$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
RET	0.26	0.10	0.08	0.96	0.94	0.99
WHSA	0.00	0.00	0.00	0.94	0.99	0.99
DIST	0.00	0.00	0.00	1.00	0.99	0.99
OEM	0.26	0.33	0.33	1.00	1.00	1.00

Finally, p-values of the difference between the number of moving average periods are listed in Table 5.11. For the forward supply chain, the difference between the 15 and 30 periods is significant at all echelons. In the case of the closed-loop supply chain and return estimation methods, the number of moving average periods is significant at the retailer, wholesaler, and distributor echelons, whereas the difference is insignificant at the OEM. In Figure 5.20, the change in the bullwhip at the OEM level is magnified due to the low bullwhip effect in the forward supply chain. Even the smallest changes result in high rates of increase in the bullwhip effect.

Table 5.11. P-values of the number of moving average period levels for the bullwhip effect with the forward supply chain and CLSC.

Echelons	**FSC**	**MA**	**OS**	**ARI**
RET	0.00	0.01	0.00	0.00
WHSA	0.03	0.02	0.01	0.01
DIST	0.01	0.01	0.01	0.00
OEM	0.00	0.18	0.12	0.12

The average NSA at each echelon in the forward supply chain can be seen in Figure 5.21. Net stock amplification is the lowest at the OEM echelon in the capacitated forward supply chain, as the capacity constraint limits the production and inventory variability. Net stock amplification is higher with a 15-period moving average and a longer horizon controls the stock variability better. The inventory variability increases downstream as we have observed earlier, and the trend is consistent for both levels of the number of moving average periods parameter.

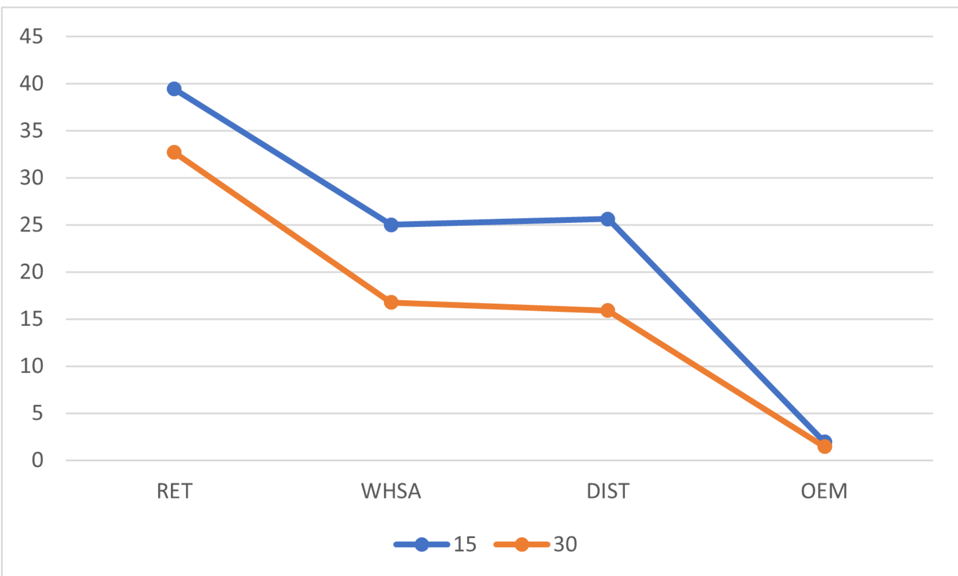
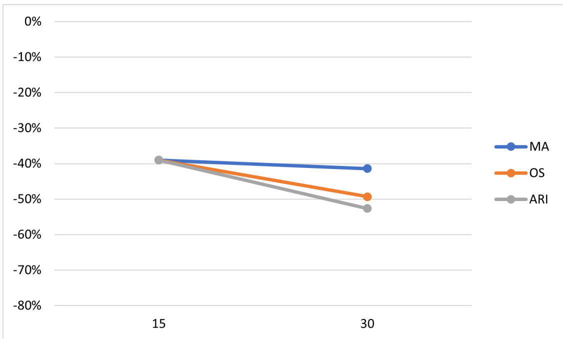
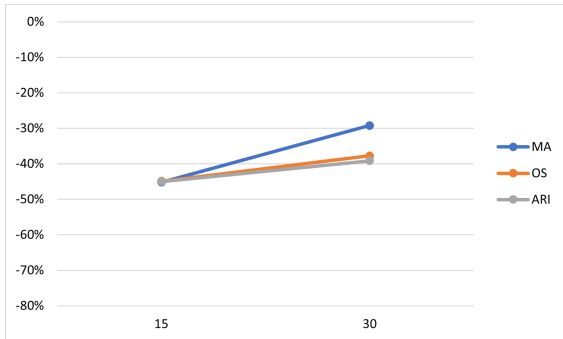


Figure 5.21. Main effect of the number of moving average periods on NSA in the forward supply chain.

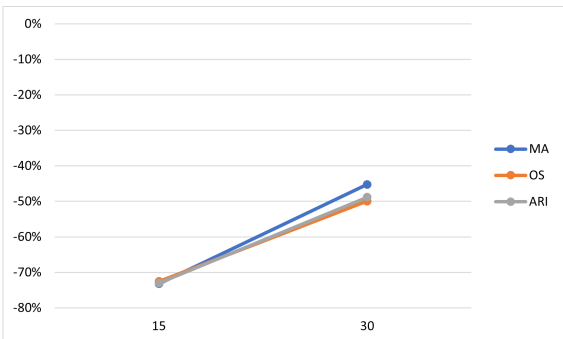
Figure 5.22 summarizes the change in NSA with the return flow. We observe similar results for all echelons to the bullwhip effect. Return estimation with orbit size information and advanced return information produces better results than the moving average with 30 periods, but the difference is insignificant with a 15-period moving average for the demand and return forecasting.



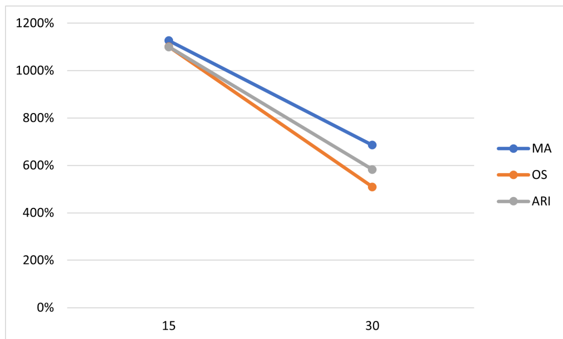
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.22. Main effect of the number of moving average periods on the average change in NSA from the forward supply chain.

Table 5.12 demonstrates the p-values of Tukey's range test for the forward and closed-loop supply chain with the 15-period moving average. In this setting, the return flow has a significant impact on the net stock amplification at all echelons, but the difference between the return estimation methods is insignificant.

Table 5.12. P-values for the net stock amplification, $m = 15$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
RET	0.00	0.00	0.00	0.99	0.99	0.99
WHSA	0.00	0.00	0.00	0.99	0.98	0.98
DIST	0.00	0.00	0.00	1.00	0.99	0.99
OEM	0.05	0.02	0.02	1.00	0.99	0.98

Table 5.13 demonstrates the significance of the return flow and return estimation methods with the 30-period moving average. The significance of the return flow is similar at the retailer, wholesaler, and distributor echelons, but the increase in the net stock amplification is insignificant with the longer forecast horizon at the OEM level.

Table 5.13. P-values for the net stock amplification, $m = 30$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
RET	0.00	0.00	0.00	0.91	0.78	0.99
WHSA	0.01	0.00	0.00	0.97	0.89	0.99
DIST	0.00	0.00	0.00	0.99	0.99	0.99
OEM	0.18	0.42	0.31	0.96	0.99	1.00

Finally, Table 5.14 displays the significance between the number of moving average periods for the forward and closed-loop supply chains. In the forward supply chain, the number of moving average periods has a significant impact on the net stock amplification for all echelons. The number of periods is significant with the moving average return estimation at the wholesaler and distributor echelons as this parameter is used for both demand and return forecast in this setting.

Table 5.14. P-values of the number of moving average period levels for the net stock amplification with the forward supply chain and CLSC.

Echelons	**FSC**	**MA**	**OS**	**ARI**
RET	0.01	0.75	0.28	0.13
WHSA	0.00	0.02	0.07	0.06
DIST	0.00	0.03	0.03	0.03
OEM	0.00	0.13	0.07	0.07

Figure 5.23 shows the main effect of the number of moving average periods on the average fill rate at each echelon. The average fill rate mostly decreases upstream as the retailer is only echelon without back orders and the customer demand arrives one by one. The longer moving average horizon for demand and return forecasting produces higher fill rates for the retailer, wholesaler, and distributor, but the its impact is insignificant at the OEM echelon.

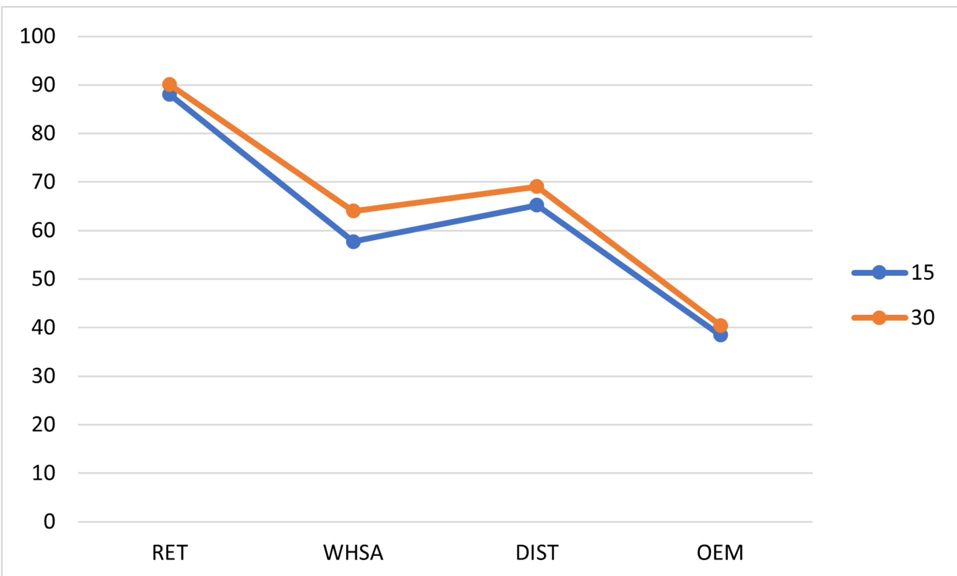
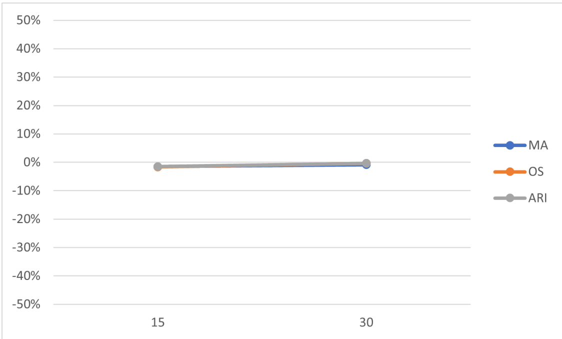
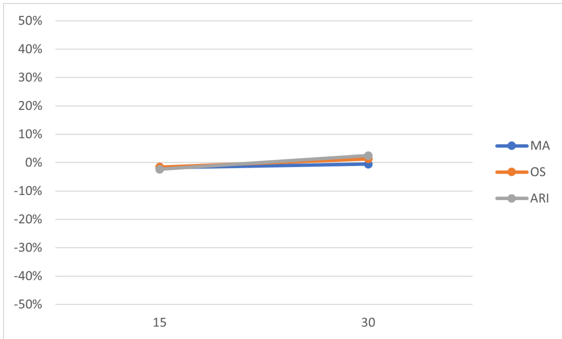


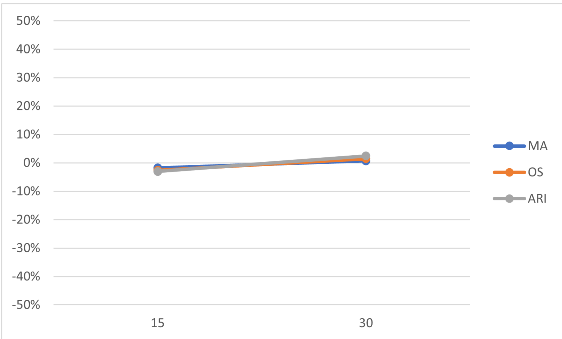
Figure 5.23. Main effect of the number of moving average periods on AFR in the forward supply chain.



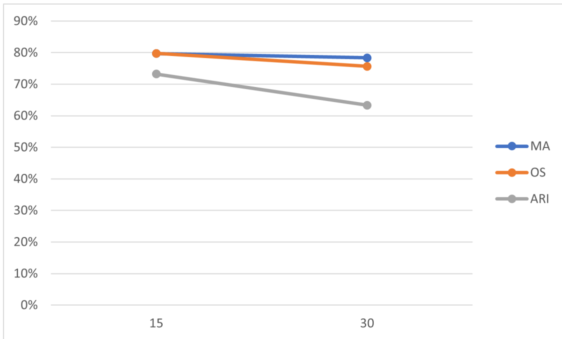
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.24. Main effect of the number of moving average periods on the average change in AFR from the forward supply chain.

Figure 5.24 summarizes the main effect of the number of moving average periods on the change in the average fill rate with the return flow. The return flow does not have a significant impact on the average fill rate for any level of the number of moving average periods at the retailer, wholesaler, and distributor echelons. The OEM is the only echelon to be affected by the return flow in terms of average fill rate. The number of moving average periods does not have a significant impact on the average fill rate at the OEM echelon.

Figure 5.25 shows the average order cycle time in the forward supply chain for the levels of the number of moving average periods. The order cycle for the wholesaler-retailer echelons is similar for both levels of the moving average periods. However, the 15-period moving average causes longer deliveries at the upstream echelons. The order cycle time between the distributor and wholesaler is shorter since the distributor creates a buffer between the downstream echelons and the capacitated production flow.

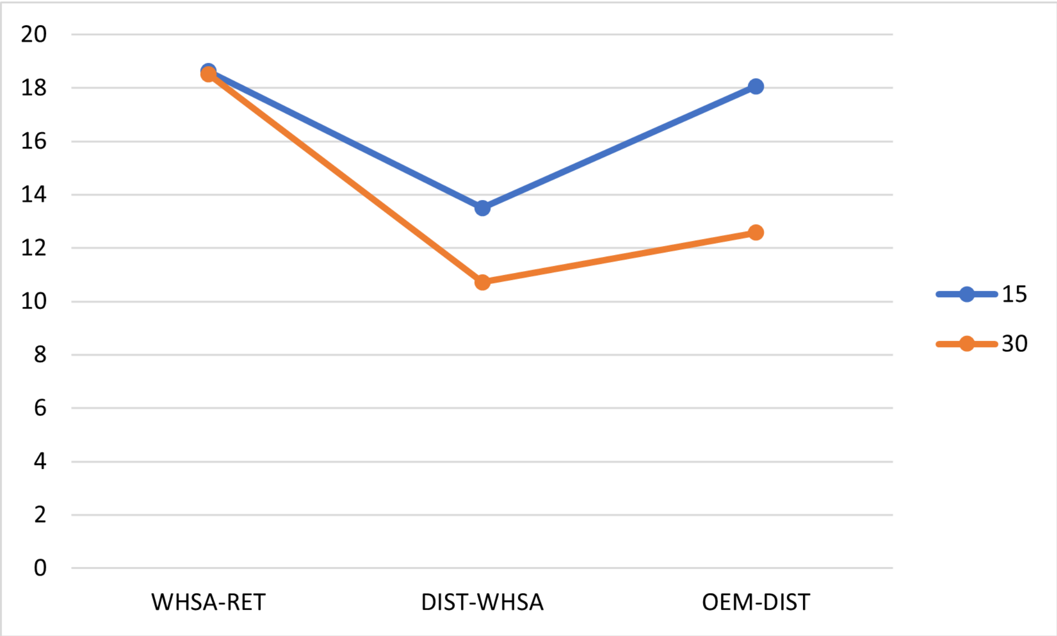
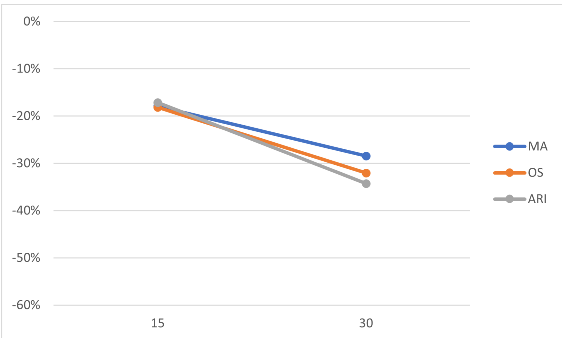


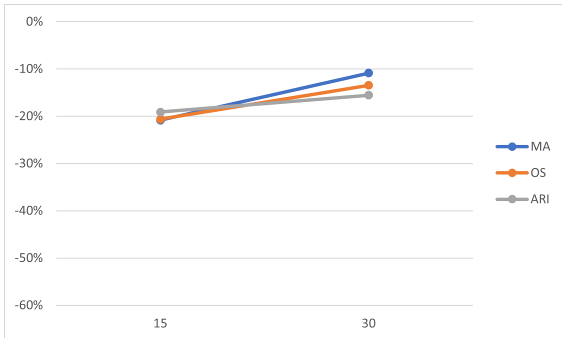
Figure 5.25. Main effect of the number of moving average periods on the order cycle time in the forward supply chain.

Figure 5.26 demonstrates the main effect of the moving average periods on the change for the order cycle time with the return flow. Although the wholesaler-retailer and distributor-wholesaler cycles see a 20% decrease in the bullwhip effect with the 15-period moving average, the difference is significant only for the former. The distributor-wholesaler cycle is much shorter than the downstream delivery time, so the similar rate of change is not at a similar significance level. For the OEM-distributor deliveries, the return flow creates a significant difference due to the additional inventory from remanufacturing.

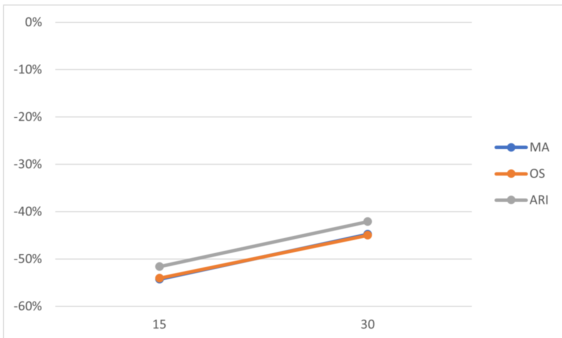
Table 5.15 summarizes the results of Tukey's range test with $m = 15$. The p-values indicate the significance of the difference between the forward supply chain and the return estimation methods. At $\alpha = 0.05$ significance level, the difference between the forward supply chain and all return estimation methods is significant for the wholesaler-retailer order cycle time. However, the difference between the return estimation methods is not significant. We observe similar results for the order cycle time between the OEM and distributor. However, the difference between the forward supply chain and return estimation methods is insignificant for the distributor-wholesaler order cycle. The order cycle time is the shortest between these echelons and the return flow does not improve this performance measure significantly.



(a) Wholesaler-Retailer



(b) Distributor-Wholesaler



(c) OEM-Distributor

Figure 5.26. Main effect of the number of moving average periods on the average change in order cycle time from the forward supply chain.

Table 5.15. P-values for the order cycle time, $m = 15$.

Echelons	**FS-MA**	**FS-OS**	**FS-AR**	**MA-OS**	**MA-AR**	**OS-AR**
WHS-RET	0.03	0.03	0.05	0.99	0.93	0.92
DIS-WHS	0.06	0.08	0.09	0.97	0.86	0.90
OEM-DIS	0.00	0.00	0.00	1.00	1.00	1.00

Table 5.16 summarizes the p-values of the difference between the forward supply chain and closed-loop supply chain return estimation methods with a 30-period moving average. The significance of the differences between the model scenarios is similar to the 15-period level, but in the wholesaler-retailer order cycle, the return flow is more significant than in a 15-period moving average scenario.

Table 5.16. P-values for the order cycle time, m = 30.

Echelons	FS-MA	FS-OS	FS-AR	MA-OS	MA-AR	OS-AR
WHS-RET	0.00	0.00	0.00	0.57	0.38	0.73
DIS-WHS	0.33	0.19	0.12	0.99	0.94	0.99
OEM-DIS	0.00	0.00	0.00	1.00	0.98	0.98

Table 5.17 lists the p-values of the difference between the number of moving average periods for the forward and closed-loop supply chain. In the forward supply chain, the difference between the 15 and 30 periods is significant for the cycles distributor-wholesaler and OEM-distributor. For the return estimation methods, the difference between the number of moving average periods is insignificant for any order cycle at α = 0.05.

Table 5.17. P-values of the number of moving average period levels for the order cycle time with the forward supply chain and CLSC.

Echelons	FSC	MA	OS	ARI
WHS-RET	0.15	0.38	0.18	0.10
DIS-WHS	0.02	0.29	0.18	0.09
OEM-DIS	0.00	0.41	0.39	0.37

5.2.1.4. Average Product Lifetime. In this section, we analyze the impact of the average product lifetime. We present the main effect of exponentially distributed product lifetime with rates of 360 and 1080 days on the bullwhip effect, net stock amplification, average fill rate, and order cycle time. Fast-consumption products are returned to the forward supply change in a shorter period of time and the lifetime variance of the slow-consumption product is higher according to the exponential characteristics.

Figure 5.27 shows the average bullwhip effect of the echelons for the levels of the product lifetime. The bullwhip effect is higher with the shorter product lifetime at the wholesaler and distributor echelons, but the difference is insignificant at the retailer and OEM.

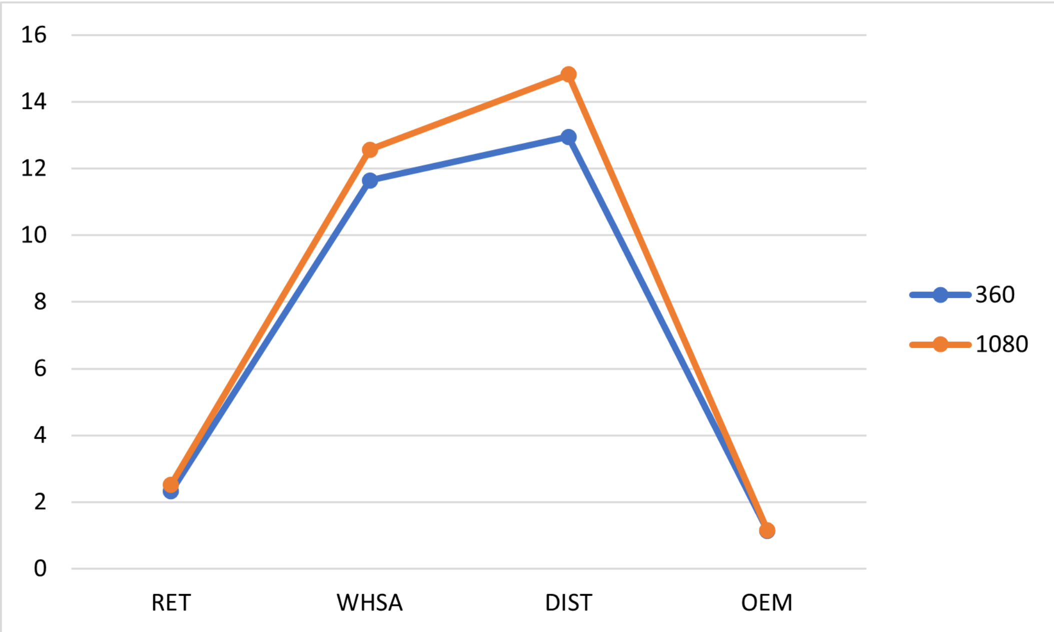
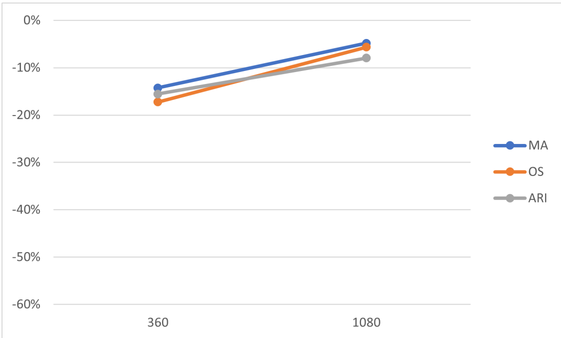
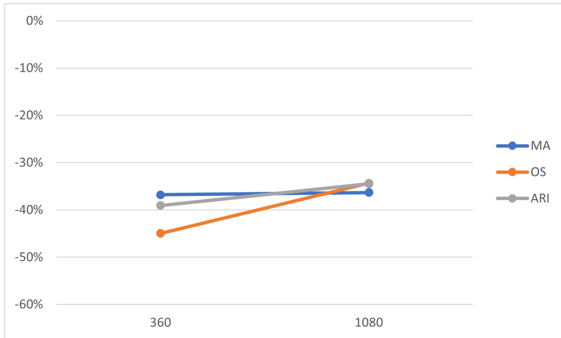


Figure 5.27. Main effect of the average product lifetime on BWE in the forward supply chain.

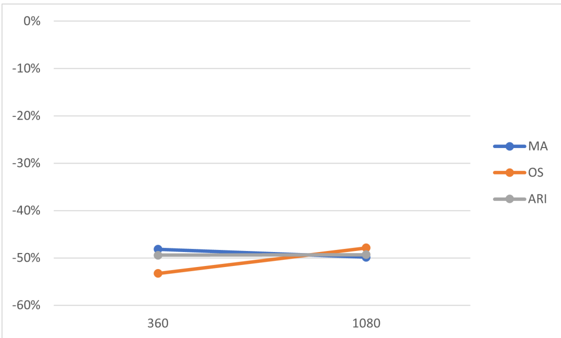
Figure 5.28 summarizes the change in the bullwhip effect for the average product lifetime. Although the change in the bullwhip effect with the return flow is similar for the product lifetimes, the impact of the average product lifetime levels persists for the return estimation method at the wholesaler and distributor levels. Although the change in the bullwhip effect seems high in Figure 5.28, it is exaggerated due to the already low order variability. The difference between the return estimation methods is insignificant for all echelons.



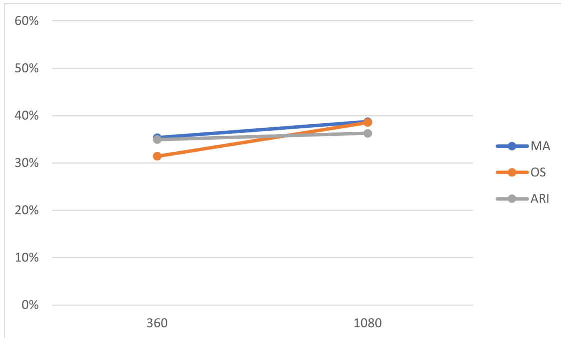
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.28. Main effect of the average product lifetime on the average change in BWE from the forward supply chain.

The average product lifetime does not have a significant impact on the bullwhip effect, net stock amplification, average fill rate, and order cycle time. Since we are analyzing the supply chain under steady-state conditions, the return arrivals converge to a comparable quantity. Table 5.18 lists the p-values for the average product lifetime level for the forward supply chain and return estimation methods. These results are consistent with the study by Adenso-Diaz *et al.* [31], where the authors argued that the average product lifetime does not have a significant impact on the bullwhip effect. In conclusion, the impact of the average product lifetime is insignificant for longer horizons in a capacitated closed-loop supply chain, but it should be noted that we assumed exponentially distributed product lifetime. The results could be different for other distribution where the coefficient of variation is not equal to 1.

Table 5.18. P-values of the average product lifetime levels for BWE with the forward supply chain and CLSC.

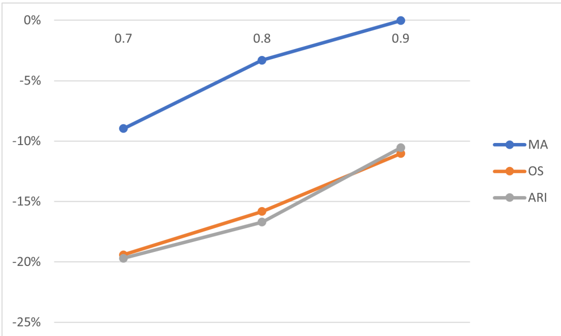
Echelons	**FSC**	**MA**	**OS**	**ARI**
RET	0.35	1.00	0.79	0.96
WHSA	0.37	0.70	0.56	0.93
DIST	0.48	0.71	0.67	0.99
OEM	0.96	0.90	0.98	0.86

5.2.2. Impact of Other Experimental Settings

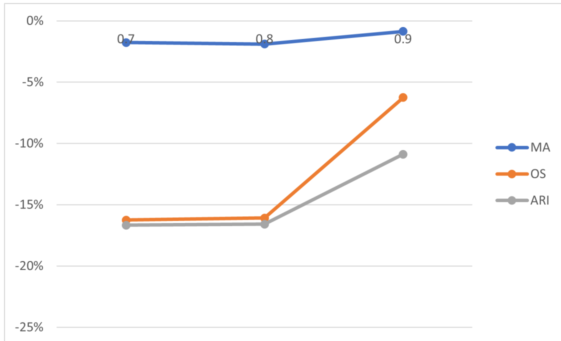
In this section, we analyze the impact of the desired service level, product lifetime variability, and alternative shipment policies. We set the previously analyzed parameters to levels at which the supply chain is less affected so that the impact of these new settings is more evident in the experiments. The reorder period r is set to 15 days as the change in the bullwhip effect was smaller. The number of moving average periods m is set to 30 for the same reason.

We take the return probability p as 0.5 to observe the changes with mid-level return flow. The average product lifetime γ is set to 720 days as the impact of this parameter resulted in varying impacts for the levels analyzed, so we experiment with a value in between. We repeat the same simulation setting for the simulation length, the warm-up period, and the number of batches. We present the change in the bullwhip effect from the forward supply chain to the return estimation methods.

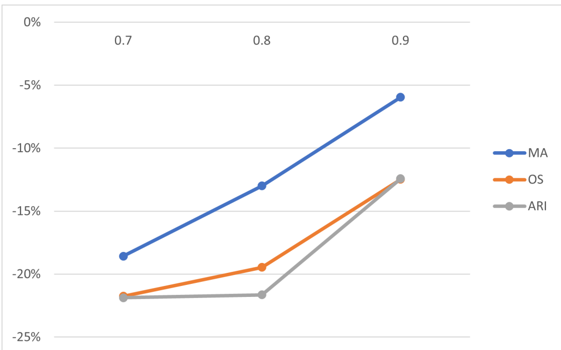
5.2.2.1. Desired Service Level. The desired service level (DSL) is the target order fulfillment rate for the supply chain echelons. The desired service level is factored into the safety stock calculation. Higher DSL leads to extra safety stock so that the inventory levels are protected from demand and return variability. We experiment with decreasing service levels to observe its impact on the bullwhip effect. The results are presented as the percent change from the forward supply chain with the return estimation methods at each echelon.



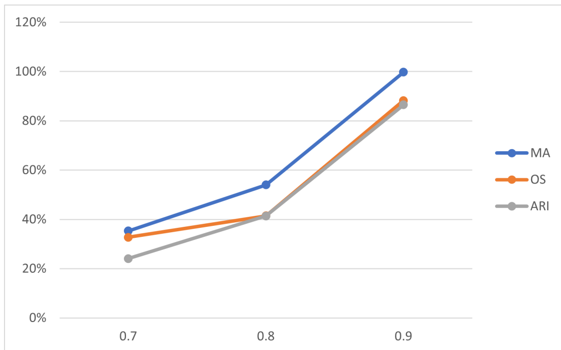
(a) Retailer



(b) Wholesaler



(c) Distributor



(d) OEM

Figure 5.29. Change in the bullwhip effect at each echelon for DSL = (0.7, 0.8, 0.9), r = 15, p = 0.5, m = 30, γ = 720.

Figure 5.29 demonstrates the change in the bullwhip effect for the desired service levels 0.7, 0.8, and 0.9. At each echelon, return estimation with the moving average results in less improvement in the bullwhip effect compared to the estimation methods using information. Return flow improves the bullwhip effect more with decreasing desired service levels. The echelons have lower levels of safety stock when operating with lower desired service levels, so the shipment delays and limited product supply severely affect the inventory levels. Therefore, the return flow has a more visible impact on these policies. Investing in information is also advantageous with lower desired service levels as the difference between the moving average and the other two methods is significant.

5.2.2.2. Product Lifetime Variability. In this section, we compare the performance of return estimation with the orbit size information for different product lifetime distributions. As explained in the Methodology chapter, the orbit size information assumes the returns are exponentially distributed. We experiment with different product lifetime distributions and lifetime variability values from the exponential, log-normal, and Weibull distributions and compare the impact of the lifetime distribution on the bullwhip effect.

We set the average product lifetime to 720 days and experiment with different coefficient of variation values for the log-normal and Weibull distributions. Since the coefficient of variation of the exponential distribution is 1, different levels of product lifetime variability affect the performance of the orbit size information. We first introduce the statistical properties of the exponential, log-normal, and Weibull distributions and their use in reliability engineering. Then, we compare the performance of return estimation with orbit size information for different lifetime distributions and lifetime variabilities. The model parameters are set to $r = 15$, $p = 0.5$, $m = 30$, $\gamma = 720$, and $DSL = 0.9$.

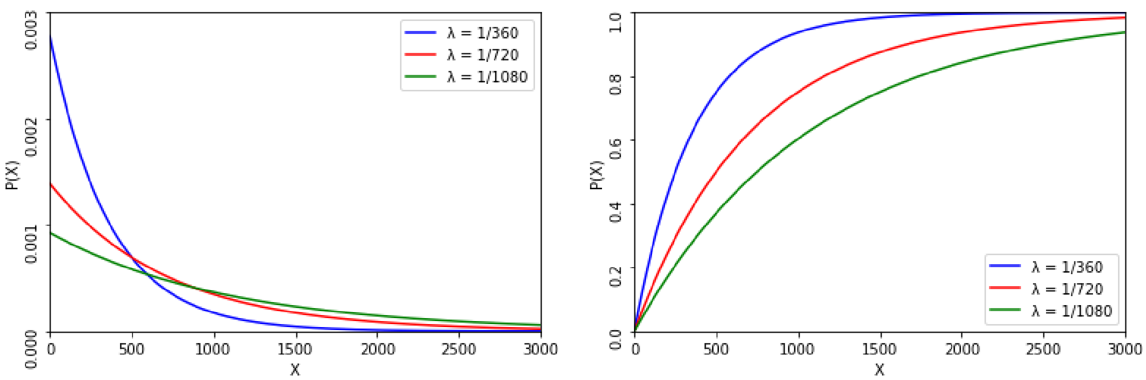
Service life in reliability engineering is defined as the time the product will be in service before it fails or requires repair. Service life is predicted with statistical models which provide the probability distribution of the service life. Exponential distribution has been shown to model failures, the log-normal distribution is commonly used to model repair times, and the Weibull distribution can be used to model various deterioration behaviors with its shape parameter.

The lifetime distribution of products models the expected failure rate and service life characteristics. The exponential, log-normal, and Weibull distributions are frequently used in reliability for various product lifetime scenarios. The expected value and variance of these distributions are given in Table 5.19.

Table 5.19. Expected value (mean) and variance of lifetime distributions.

Distribution	**Mean**	**Variance**
Exponential(λ)	$1/\lambda$	$1/\lambda^2$
Log-normal(μ, σ^2)	$\exp(\mu + \sigma^2/2)$	$[\exp(\sigma^2) - 1] \cdot \exp(2\mu + \sigma^2)$
Weibull(λ, k)	$\lambda\,\Gamma(1 + 1/k)$	$\lambda^2 \left[\Gamma\left(1+\frac{2}{k}\right) - \left(\Gamma\left(1+\frac{1}{k}\right)\right)^2\right]$

In addition to the aforementioned attributes of the exponential distribution, constant failure rate and empirical tests on reliability demonstrating appropriate representation make it a practical distribution [63]. The constant failure rate of the exponential distribution is equal to its rate parameter λ, and the mean time to failure (MTTF) is the inverse of the failure rate. The memoryless property indicates the reliability of the component is a function of the service duration, and does not depend on the time elapsed. The probability density and cumulative distribution functions of exponential distribution with different rate parameters are given in Figure 5.30.

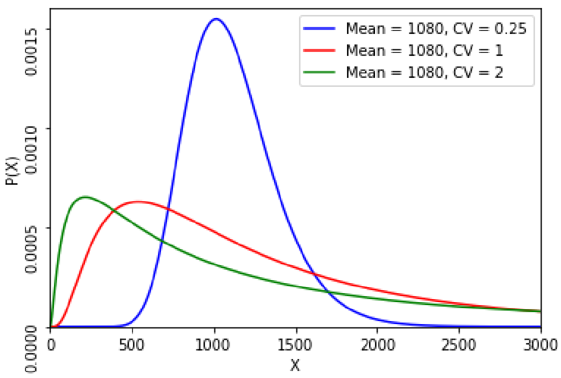


(a) Probability density function

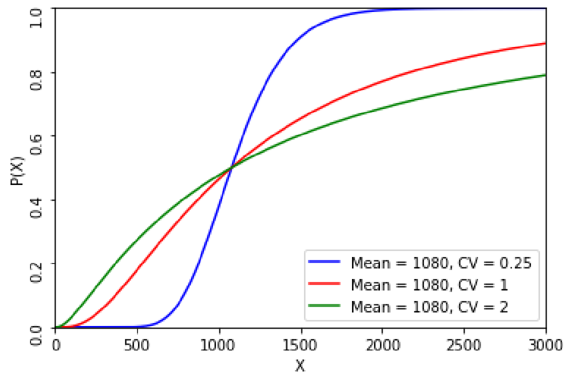
(b) Cumulative distribution function

Figure 5.30. Probability functions of exponential distribution with a mean lifetime of 1, 2, and 3 years.

The log-normal distribution is another distribution with widespread use in reliability models. The logarithm of a normally distributed random variable follows the log-normal distribution. The log-normal distribution is particularly useful to model component failure due to degradation, stress, or fatigue as the likelihood of failure peaks early on before decreasing.



(a) Probability density function



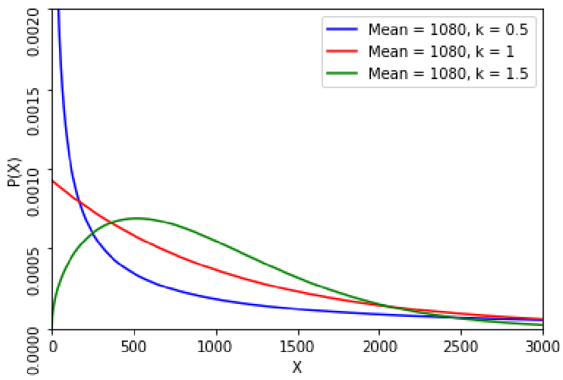
(b) Cumulative distribution function

Figure 5.31. Probability functions of log-normal distribution with the coefficient of variation of 0.25, 1, and 2.

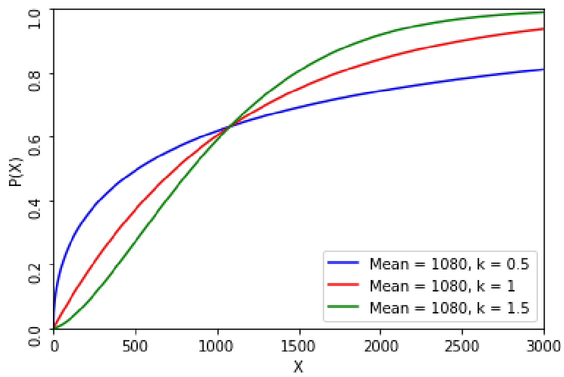
The log-normal distribution can represent time-to-repair or component return when the data shows early failure or wear out. In order to model the distribution with a given mean and variance, the parameters are transformed using the coefficient of variation. The probability density and cumulative distribution functions of exponential distribution with different coefficient of variation parameters are given in Figure 5.31.

Finally, the Weibull distribution is a flexible lifetime distribution, deriving various characteristics with the shape parameter k. The shape parameter value can form the reliability and failure behavior. When $0 < k < 1$, the failure rate decreases with time, indicating early life failure. $k = 1$ models the exponential distribution, and has a constant failure rate. $k > 1$ demonstrates an increasing failure rate with time, representing wear-out failure.

With varying k values, the three stages of lifetime distribution in the bathtub curve can be modeled. Figure 5.32 shows the related probability functions of the Weibull distribution. In order to experiment with different coefficient of variation values, we make an approximation to transform the shape parameter to the coefficient of variation $CV = 1 / k$ where CV is the coefficient of variation and k is the shape parameter of the Weibull distribution, as shown by Tanaka and Ichikawa [64].



(a) Probability density function



(b) Cumulative distribution function

Figure 5.32. Probability functions of Weibull distribution with different shape parameters.

We first model exponentially distributed product lifetime and change the lifetime distribution to log-normal and Weibull distributions with different coefficients of variation to investigate whether the lifetime distribution and lifetime variability have an impact on the performance of return estimation with orbit size information. We assume a two-year average product lifetime for all lifetime distributions and lifetime variability scenarios.

Figure 5.33 displays the bullwhip effect at supply chain echelons when return flow is estimated with orbit size information and the product lifetime is exponentially distributed. The wholesaler experiences the highest order variability, followed by the distributor. Retailer's order variability is much lower than the wholesaler and distributor as the ultimate downstream echelon and the OEM's production is leveled by the capacity constraint.

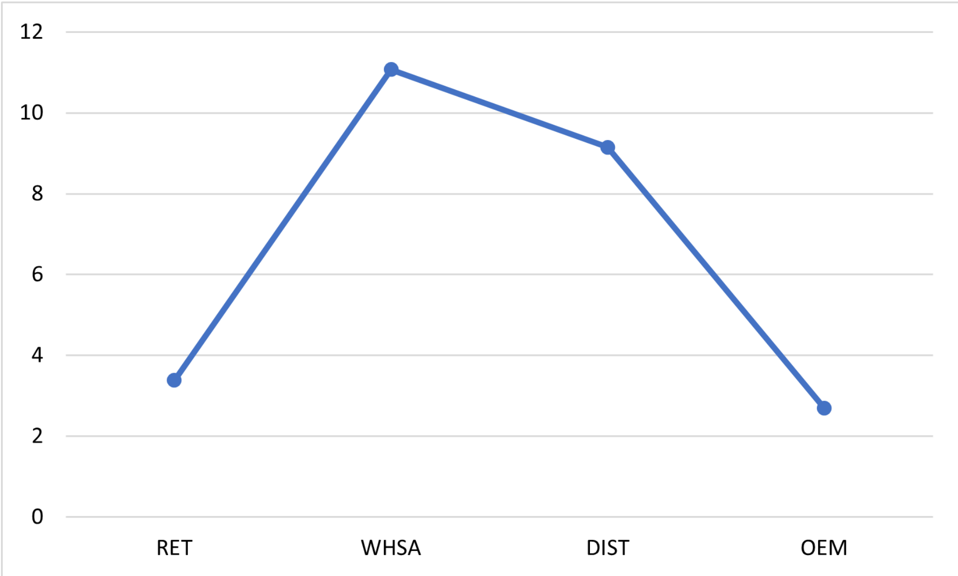


Figure 5.33. BWE with orbit size return estimation $PLD = Exponential(1/720)$, $r = 15$, $p = 0.5$, $m = 30$, $DSL = 0.9$.

Figure 5.34 demonstrates changes in the bullwhip effect at each echelon for the different coefficient of variation values of the log-normal distribution. The bullwhip effect is not affected at the retailer, distributor, and OEM levels when the product lifetime variability is low. The wholesaler's order variability slightly increases when the lifetime distribution is log-normal. Since the wholesaler had the highest bullwhip effect even when the lifetime is exponentially distributed, vulnerability against any change is expected at this echelon. The bullwhip effect increases at all echelons as the coefficient of variation increases, since the return variability increases the uncertainty in the return flow and decreases the accuracy of return estimation.

Figure 5.35 summarizes changes in the bullwhip effect when the lifetime distribution is Weibull. Since the Weibull distribution reduces to the exponential distribution when $CV = 1$, we do not observe a change in the bullwhip effect. However, the bullwhip effect increases even with the lowest coefficient of variation at each echelon with the Weibull distribution. The impact of higher levels of coefficient of variation is greater than the log-normal distribution.

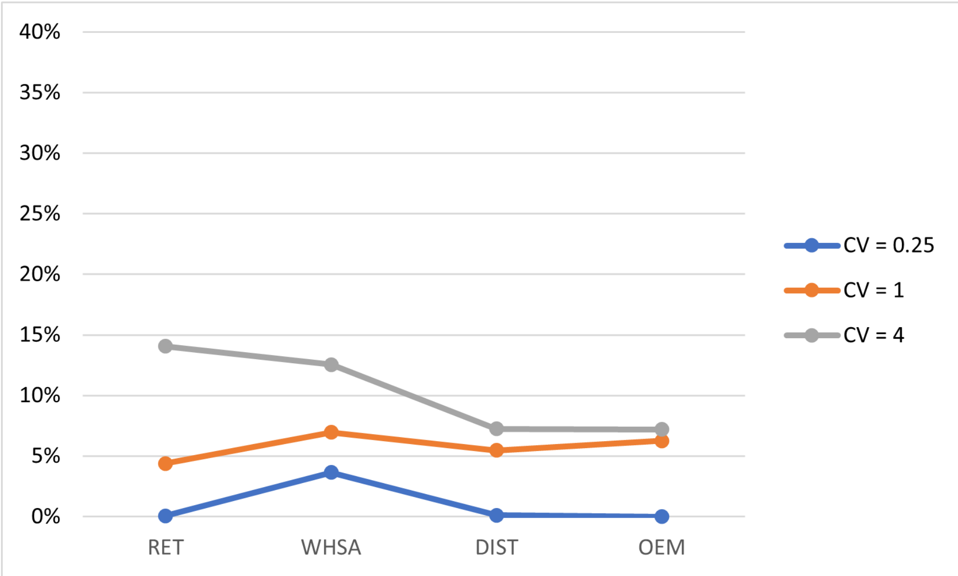


Figure 5.34. Changes in the bullwhip effect with orbit size return estimation from $PLD = exp(1/720)$ to $log\text{-}normal((720,\ CV = 0.25), (720,\ CV = 1), (720,\ CV = 4))$, $r = 15,\ p = 0.5,\ m = 30,\ DSL = 0.9$.

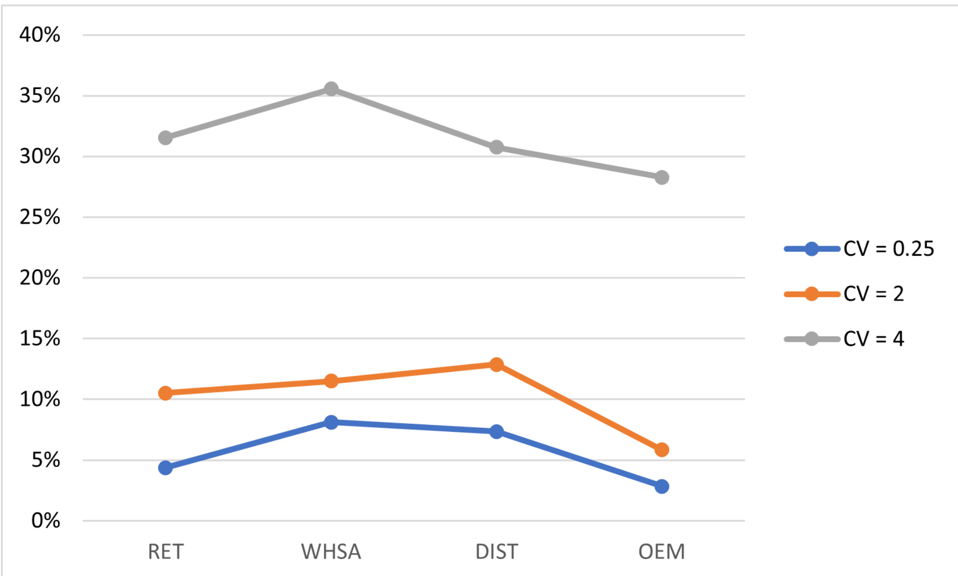


Figure 5.35. Changes in the bullwhip effect with orbit size return estimation from $PLD = exp(1/720)$ to $Weibull((720,\ CV = 0.25), (720,\ CV = 2), (720,\ CV = 4))$, $r = 15,\ p = 0.5,\ m = 30,\ DSL = 0.9$.

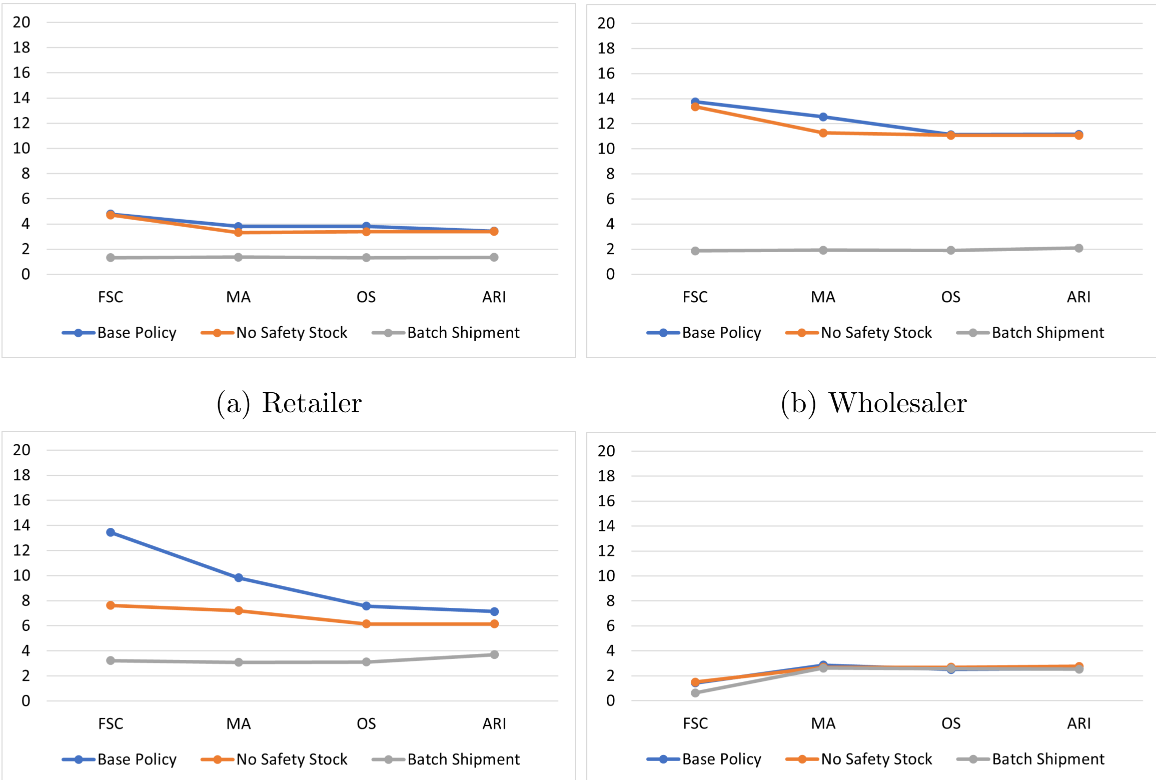
In conclusion, we can comment different product lifetime distributions and lifetime variability values have a significant impact on the accuracy of the orbit information due to exponential lifetime assumption, but the estimation is more reliable when the product lifetime distribution is log-normal rather than Weibull. Product lifetime variability is positively correlated with the bullwhip effect. Hence, the supply chain actors would benefit from a return flow with lower variability.

5.2.2.3. Alternative Shipment Policies. As described earlier, we experiment with alternative order-shipment policies to observe how different inventory replenishment and delivery processes affect the bullwhip effect. We compare the base policy to the no safety stock and batch shipment policies. No safety stock policy describes the ordering decisions with only the forecast quantity and omits safety stock surplus. In the batch shipment policy, products in stock are shipped immediately until the order is fulfilled, without waiting for the complete order quantity to appear in the inventory.

Since the order is placed before receiving demand information from the lower echelon, it is important to order the necessary quantity to meet the demand without creating excess inventory. With the capacity constraint, a delay in order fulfillment is expected, which in turn increases the delivery lead time.

Keeping excess inventory, namely safety stock, as a buffer to reduce the risk of stock-outs is essential to prevent interruptions in the supply chain, and ultimately lost sales. Periodic inventory review system (r, S) does not allow for a predetermined minimum inventory level triggering inventory replenishment, hence, safety stock compensates for the order variability, forecast inaccuracies, and delivery delays. Accurate safety stock estimation helps maintain desired service levels without excess inventory. Safety stock quantity depends on the desired service level, the average and standard deviations of historical delivery lead time, and order information.

Figure 5.36 demonstrates the bullwhip effect for the forward supply chain and three return estimation methods against different order-shipment policies at each echelon. For the retailer, not keeping safety stock does not improve the bullwhip effect significantly, but the wholesaler sees a slight improvement when the return estimation method is the moving average.



(a) Retailer (b) Wholesaler

(c) Distributor (d) OEM

Figure 5.36. BWE with different shipment policies $r = 15$, $p = 0.5$, $\gamma = 720$, $m = 30$.

No safety stock policy is advantageous at the distributor echelon for the forward supply chain and any return estimation method. The batch shipment policy, where the upstream echelons ship downstream orders in batches instead of waiting for the complete order to be available in the inventory, reduces the bullwhip effect significantly at the retailer, wholesaler, and distributor echelons.

In a capacitated production system, the product supply is more limited, and shorter delivery lead times even for a portion of the orders restrict the downstream echelons from inflating their orders to overcome the lead time uncertainties. The alternative policies do not create a significant advantage at the OEM echelon, except for the batch shipment policy with the forward supply chain.

No safety stock policy was advantageous only at the distributor echelon, as the overstated downstream orders of the base policy were constrained without the safety stock buffers. As for the batch shipment policy, more controlled back orders result in less instability in the supply chain.

On the other hand, multiple shipments increase the logistic costs, and may not be feasible to ship batches with small quantities. In our model, we do not limit the deliverable quantity, and the upstream echelons could ship batches of a single product. In an optimization problem with batching constraints and logistic costs, the batch shipment policy may not be the advisable policy.

5.3. CLSC with Impulse Demand

In this section, we analyze the supply chain under impulse demand and compare the outcome of the return estimation methods, namely the moving average, orbit size information, and advance return information. The impulse demand occurs once after the warm-up period and we observe the long-term effects in the supply chain. We assume the impulse demand lasts for 30 days and the daily demand quadruples in this period. We set the simulation duration to 10000 and the warm-up period to 1000 days. We shortened the warm-up period since we set the average product lifetime to 360 days and 1000 days is sufficient for the system to reach steady state conditions.

The total simulation duration is also shortened to investigate the more immediate impact of the impulse demand. We set the number of batches to 30, and the batch size to 300 days. The impulse demand first arrives at time 1000, at the end of the warm-up period. In the following 30 days, daily customer demand arrives on average 4 products. Average daily demand turns back to 1 product for the remainder of the simulation run. We take the batch means to determine the BWE in each experiment.

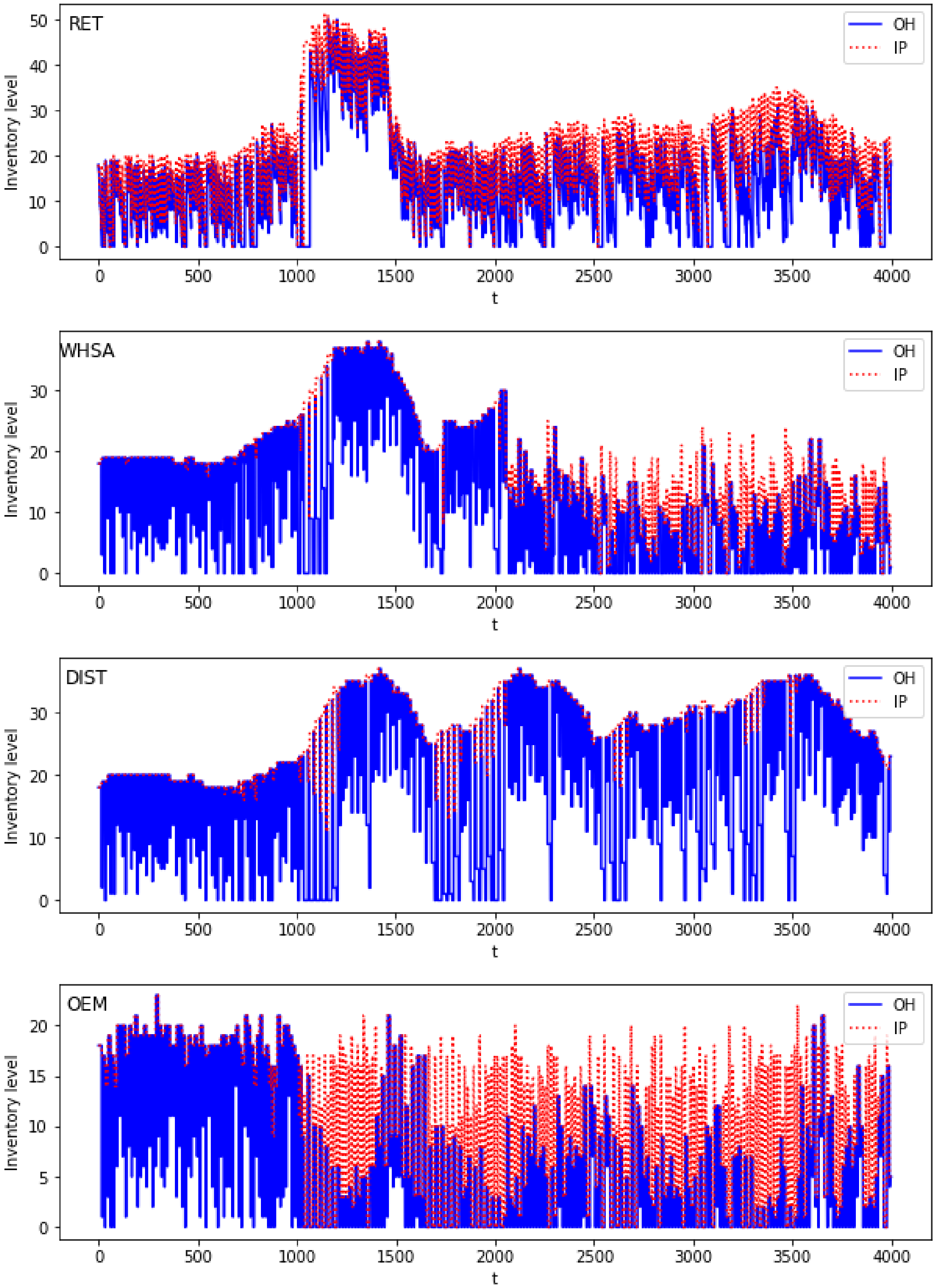
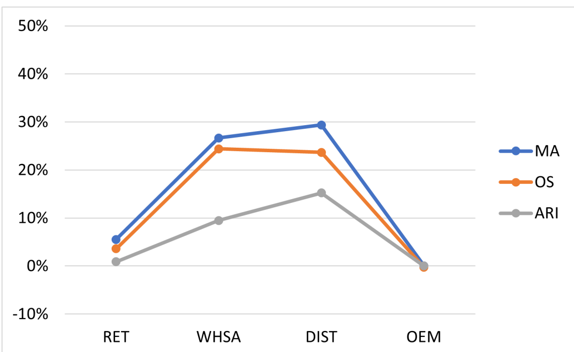
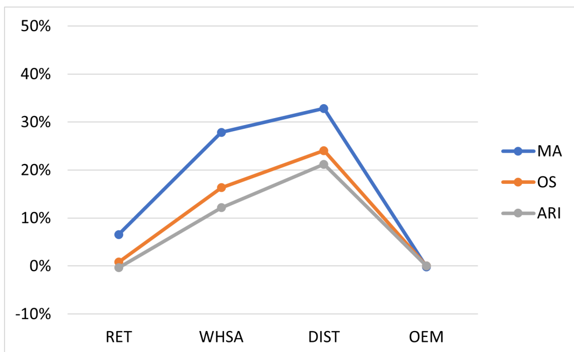


Figure 5.37. Impact of impulse demand on the inventory levels, $r = 15$, $p = 0.5$, $m = 30$, $\gamma = exp(1/720)$.

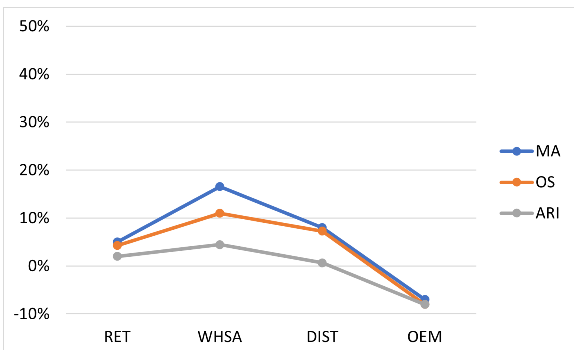
Figure 5.37 illustrates the impact of impulse demand on the inventory level at each echelon. When the impulse demand arrives, the retailer sees immediate inventory amplification. The wholesaler's inventory levels follow the fluctuation in about 60 days but experience a secondary smaller amplification. The distributor's inventory levels are affected in another 30 days, the secondary amplification is larger than that of the wholesaler, and there is a tertiary amplification. The OEM's inventory levels are dampened with the impulse demand, as the capacity constraint prevents the potential amplification, and the stock levels cannot build up due to increased demand. It should be noted that although the wholesaler and distributor experience higher inventory volatility, the magnitude of the fluctuation is higher at the retailer level. That is, the retailer faces a strong amplification and recovers, but the fluctuation at the wholesaler and distributor levels is dampened and persistent.



(a) $p = 0.1$



(b) $p = 0.5$



(c) $p = 0.9$

Figure 5.38. Impact of impulse demand on the inventory levels, $r = 7$, $p = (0.1, 0.5, 0.9)$, $m = 30$, $\gamma = exp(1/720)$.

We compare the bullwhip effect in the closed-loop supply chain without and with impulse demand. Figure 5.38 summarizes the change in the bullwhip effect with a 7-day reorder period and return probabilities 0.1, 0.5, and 0.9. Although the difference between the return estimation methods was insignificant for the supply chain parameters analyzed in this study, the return estimation method has a significant impact on the change in the bullwhip effect under impulse demand.

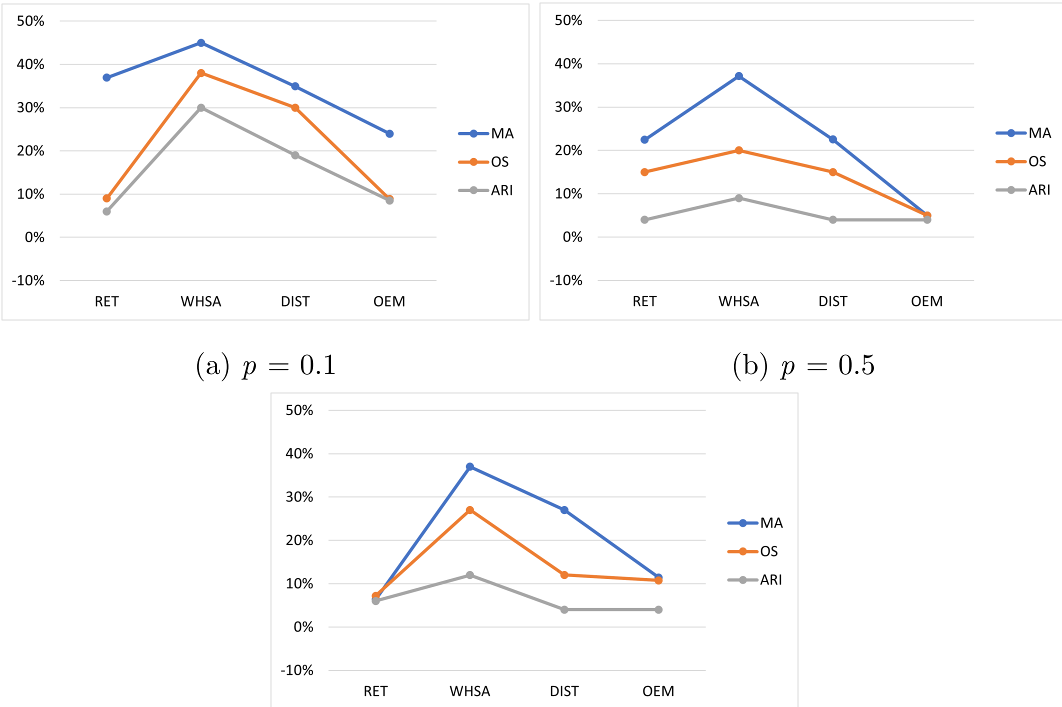
Return estimation with the orbit size and advanced return information leads to a lower increase in the bullwhip effect when there is an impulse demand. Table 5.20 shows the p-values of the ANOVA test between the return estimation methods. The change in the bullwhip effect with the impulse demand is significant for all values of the return probability except for the OEM.

The increase in the bullwhip effect is lower with a return probability of 0.9, and the bullwhip effect even decreases at the OEM level. The impulse demand increases the inventory position of the OEM due to back orders, and the capacity utilization of the OEM increases as the production tries to catch up with the waiting orders as much as the production capacity allows.

Table 5.20. P-values of the return estimation methods for p = (0.1, 0.5, 0.9), r = 7.

Echelons	**0.1**	**0.5**	**0.9**
RET	0.05	0.01	0.02
WHSA	0.00	0.01	0.01
DIST	0.01	0.01	0.03
OEM	0.99	0.99	0.99

Figure 5.39 demonstrates the change in the bullwhip effect under impulse demand for the 15-day reorder period. The increase in the bullwhip effect is higher with the longer reorder period since the production and ordering decisions slower to adjust, and the order quantity is significantly higher.



(a) $p = 0.1$

(b) $p = 0.5$

(c) $p = 0.9$

Figure 5.39. Impact of impulse demand on the inventory levels, $r = 15$, $p = (0.1, 0.5, 0.9)$, $m = 30$, $\gamma = exp(1/720)$.

The difference between the return estimation methods is significant for the retailer, wholesaler, and distributor echelons, as seen in Table 5.21. Forecasting returns with the orbit size and advanced return information is more advantageous under the impulse demand with the 15-day reorder period.

Table 5.21. P-values of the return estimation methods for $p = (0.1, 0.5, 0.9)$, $r = 15$.

Echelons	**0.1**	**0.5**	**0.9**
RET	0.01	0.01	0.06
WHSA	0.03	0.00	0.02
DIST	0.02	0.01	0.03
OEM	0.69	0.99	0.74

In this section, we analyzed the impact of the return estimation method on the bullwhip effect under impulse demand. Unlike the previous experiments, return estimation with the orbit and advanced return information is more beneficial. Orbit information has a significant impact on the bullwhip effect when we analyze shorter period of time, as the capacitated production system is more robust long term. Secondly, the fluctuations caused by the impulse demand can be dampened with return estimation using the orbit information.

6. CONCLUSIONS AND FUTURE RESEARCH

In this study, we analyzed the demand amplification in a multi-echelon closed-loop supply chain with production capacity. The return flow is an additional source of uncertainty besides the customer demand, and the order-up-to inventory replenishment policy with the periodic review illustrated the volatility in the supply chain. We first investigated the impact of various factors on order and inventory variability in the forward supply chain. Then, we compared the changes in our performance measure when return flow is introduced to the supply chain with different return estimation methods. Since the traditional return estimation methods such as the moving average does not take the correlation between past sales and returns, we introduced return forecasting using orbit information and advanced return information.

Our findings showed the smoothing effect of the production capacity for the manufacturer. The production variability was not as amplified as the downstream orders. In a capacitated closed-loop supply chain, the demand amplification upstream progressed differently than expected, since the upper echelons benefited from the capacity constraint more than the lower echelons. The return flow dampened the demand amplification for the retailer, wholesaler, and distributor, but the OEM's production variability increased with the introduction of the return flow. Higher return flows were necessary to achieve a forward supply chain bullwhip effect levels.

Return estimation with orbit information, or advanced return information, did not have a significant impact on the bullwhip effect. Under steady state conditions, accuracy of the return estimation is not a significant contributor to the uncertainties in a multi-echelon closed-loop supply chain with production capacity. The results could be different when the production capacity is dynamic. Different product lifetime distributions and coefficient of variance values had a significant impact on the bullwhip effect when orbit information is used for return forecasting. Alternative shipment policies can reduce the bullwhip effect, but the associated costs must be considered.

The return probability had varying effect on the bullwhip effect, where only the highest return rate reduced the bullwhip effect for all echelons. The reorder period had a significant impact on the forward supply chain, but not on the closed-loop supply chain. The bullwhip effect was reduced with a higher number of moving average periods. The average product lifetime did not have a significant impact on the bullwhip effect in a closed-loop supply chain under steady state conditions.

The impulse demand amplified the order variability. Return estimation with the orbit information limited the increase in order and inventory variability under impulse demand, showing the value of information when there is an unexpected change in customer demand. The companies should invest in return information if it generates economic and strategic gain. Therefore, orbit information is advantageous for a supply chain system with sudden and immediate changes in demand. The impulse demand had minimal impact on the OEM's production variability, once again demonstrating the smoothing effect of the production capacity limits.

This study can be extended with various assumptions and specifications to investigate different supply chain systems. Although we assumed the remanufactured products are as good as new, it is possible to analyze systems where the remanufactured products create a separate demand stream, or the new and remanufactured products compete. The potential cannibalization of new product demand is interesting, as the market could shift to predominantly pre-owned products, the products returned are harder to recover.

All return products are remanufactured in the current model, but the impact of uncertainties in returned product quality or remanufacturability can be explored. The addition of inspection and sorting to determine the condition and processing would enact a more realistic closed-loop supply chain operation. Depending on the condition of the returned core, the next step could be refurbishing, disassembling, remanufacturing, material recovery, or recycling, each process handled with varying lead times. Seasonal demand and non-deterministic lead times could also be investigated in the future.

We can structure customer loyalty in a way that the lifespan of the product affects the consumer's decision to buy a new product while returning their end-of-life item. Consumers are more likely to repeat purchases if they are satisfied, and the product service life is an important factor in their buying behavior. In such model, the average product lifetime or product lifetime variability could have a significant impact on the bullwhip effect. We also assumed the daily demand is identical for products with different lifespans, but it is possible to modify the customer arrival with respect to the average product lifetime. The daily demand for long-lasting products would be less than fast consumption goods.

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APPENDIX A: APPENDIX A

$Var(Z) = E[Y] \cdot Var(X) + (E[X])^2 \cdot Var(Y)$ since $\bar{X}$ is defined as the summation of independent random variables D_i with the same distribution as D, conditioned on the event that $\bar{L} + r = n$.