On the dynamics of return collection in closed-loop supply chains

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Abstract

The effective operation of closed-loop supply chains (CLSCs) can help companies achieve sustainability goals and boost economic performance. Critical metrics of CLSCs are related to the bullwhip effect, which determines their cost efficiency and service quality. In practice, CLSCs must collect used products, a complex process that is often constrained by collection station capacity. However, how collection station capacity influences the bullwhip effect and the dynamic performance of CLSCs remains unclear. Here, we develop a system dynamics model for CLSC that integrates traditional manufacturing with remanufacturing and explore the effects of the stochastic capacity constraint of the collection station on the CLSC bullwhip effect. Using simulation and experimental techniques, we find that, generally speaking, a collection station with looser or more stable capacity constraints tends to reduce bullwhip and improve customer service regarding CLSCs. However, pertinent interactions emerge between the relevant parameters; in some situations, reducing the capacity level of a collection station may be reasonable and beneficial when the stochastic capacity constraint is very stable, or customer demand is highly variable. We also consider the partial backlog in return collection, a phenomenon associated with the stochastic capacity constraint of a collection station, and identify a new trade-off between CLSC sustainability and economic performance. Ultimately, our findings provide evidence that will guide managers' plans for the capacity management of return collection in CLSCs.

Keywords: Closed-loop supply chains, System dynamics, Bullwhip effect, Stochastic capacity constraint, Partial backlog in the return collection.

1. Introduction

In recent decades, concerns about critical environmental issues, including resource scarcity, waste management and greenhouse gas emissions, have driven discussion and implementation of closed-loop supply chains (CLSCs), a business practice that has been well received by industry and academia for maintaining resource use for as long as possible (Kazemi et al., 2019). CLSCs integrate reverse logistics processes, such as recycling, used product collection and remanufacturing, enabling companies to reach their sustainability goals by reducing their environmental effects.

However, common wisdom suggests that adopting CLSCs will decrease a company's economic profit. Although it is important to acknowledge that there are numerous economic opportunities derived from CLSCs (see Abbey and Guide, 2017), it is true that closing the loop is often expensive. This process involves the choice and implementation of a collection channel (Hong et al., 2013), and it also requires the design of mechanisms that will incentivise the return of used products (Goltsos et al., 2019). Meanwhile, CLSCs are subject to a wider range of uncertainties than traditional supply chains because of uncertainty in the quantity and quality of the collected products (Ponte et al., 2021).

Under these circumstances, efficient operation of CLSCs is an essential catalyst for increasing circularity in modern economies. To achieve high operational performance, a CLSC must reach the desired service level with low operational costs. Both perspectives (i.e. service level and operational costs) can be investigated fruitfully by studying the dynamic behaviour (e.g. bullwhip effect) of CLSCs (Goltsos et al., 2019). Previous literature shows that ineffective dynamic behaviours and the high bullwhip effect of CLSCs are significantly associated with frequent machine ramp ups and ramp downs, excessive inventory levels, and frequent staff turnover, which eventually leads to low customer service levels and high operational costs (Disney et al., 2008; Lin et al., 2017). Therefore, controlling the bullwhip effect and dynamic behaviour of CLSCs is vital to enhance operational performance and efficiency (Hosoda and Disney, 2018).

However, research on the dynamics of CLSCs is minimal compared with research on traditional systems (Goltsos et al., 2019). This is even more limited with regard to the dynamics of the return collection process and its associated different uncertainties—one of the main drivers of the bullwhip effect in CLSCs (Ponte et al., 2019, 2020a). In practice, the capacity of return collection can often be constrained, with only a proportion of the returned products collected (Georgiadis and Athanasiou, 2013). For instance, garment consumption is approximately 14 million tonnes per year in the United States, and the majority of products are sent to landfill or are incinerated after use. This means that more than USD 500 billion of value is lost each year because of the lack of collection and recycling capacity, as well as for cultural reasons (The Billie, 2021).

Therefore, determining how CLSCs can achieve high operational performance and thus a low bullwhip effect under a capacitated return collection process is vital, but the literature has largely ignored this angle (Goltsos et al., 2019). To the best of our knowledge, only one work in the CLSC dynamics literature (namely, Tombido et al., 2021) considers the capacity constraint of collection centres on the CLSCs bullwhip effect. However, the authors' modelling is oversimplified and cannot fully reflect the properties of the situation. Therefore, we highlight that the actual implications of the capacitated collection process on the dynamics of CLSCs are largely unknown.

To further uncover the effects of collection station capacity constraint on the dynamics of CLSCs, we focus on two specific research gaps. First, we explore the effects of the stochastic capacity constraint of a collection station (SCCC) on CLSCs' bullwhip effect. SCCC means that when collecting customers returns, the collection capacity of a collection station or collection centre are stochastically constrained and keep changing in different periods. In practices, this usually reflects the change of the workforces, capacity of collection vehicles, or storage spaces of return collection stations (Easwaran and Üster, 2009; Katami et al., 2015). Currently, how constraints relate to return collection in previous CLSC bullwhip and dynamics research is not clearly characterised as a fixed capacity (i.e. deterministic capacity). Rather, capacity often varies over time (i.e. stochastic capacity), particularly in the current business context defined by common supply chain disruptions. Therefore, considering the stochasticity of collection constraints has significant practical value. Second, we investigate the effect of a partial backlog in return collection (PBRC) on the bullwhip of CLSCs. PBRC is a phenomenon associated with SCCC, one that is ignored in the existing literature. It depicts a situation in which customers who want to return used products may behave in different ways when they cannot do this because of capacity restrictions. Some may be willing to wait for the next opportunity to return the product (Tombido et al., 2021), while others may simply dispose of the product (Georgiadis and Athanasiou, 2013). Both issues (i.e. SCCC and PBRC) can affect return collection and the reverse flow of materials considerably, and eventually CLSC performance.

Therefore, motivated by the practical observations and academic gaps exposed so far, the main research question explored here is expressed as follows:

How do SCCC and its associated PBRC influence the CLSC bullwhip effect?

By addressing this question, we offer a deeper understanding of how the complexity involved in capacitated return collection affects CLSCs dynamics and operational performance. Our main contributions are summarised as follows:

1. We explore the dynamics of *stochastic capacity constraint* of a collection station in closed loop supply chains by using a system dynamics approach . This extends existing literature that only focus on the deterministic static capacity constraints from system dynamics perspective. Both order and inventory dynamics are investigated, offering deep insights for their dynamic behaviour and trade-offs. Based on theoretical findings, we also provide practitioners with ‘good practice’ recommendations for designing and implementing return collection systems under stochastic capacity constraints.
2. We evaluate the influence of customer returns behaviour, i.e. *the partial backlog scenario* in return collection, on the dynamics of closed loop supply chains. Comparing the existing literature that either assumed customer returns are fully backlogged or lost, we develop a novel system dynamics model that incorporate such customer return behaviour where backlog may be partially returned. Our system dynamics analysis uncover the influence of complicated interactions between customer behaviours and the capacity constraints of return collection on CLSC bullwhip, as well as identify a trade-off between the sustainability of economics in these systems. These novel results also have meaningful implications for CLSC management and policymaking in recycling.

To address the research questions, this paper is structured as follows. After the introduction, Section 2 reviews three relevant streams of the literature to highlight our paper’s novelty. Section 3 provides technical details of the mathematical model and the experimental design. Section 4 presents and analyses the results of the simulations. Section 5 discusses the key implications of the findings. Finally, Section 6 draws the main conclusions and proposes interesting avenues for future research.

2. Literature review

To demonstrate the contribution of this paper to the previous literature, it is necessary to review the following three highly relevant streams of existing studies. The first is the bullwhip effect and dynamic perspectives in CLSCs. The second addresses the capacity constraints of CLSCs. The third relates to a partial backlog in forward supply chains and CLSCs.

2.1 The dynamics of closed-loop supply chains

The research on supply chain dynamics, particular the bullwhip effect, has been very active since the 1990s. However, compared with traditional forward supply chains, the bullwhip effect of CLSCs has not been explored as much (Goltsos et al., 2019).

Tang and Naim (2004) provided the first paper to explicitly study the bullwhip effect from a CLSC perspective. They compared how different information transparency levels can influence the bullwhip effect of these systems. Zanoni et al. (2006) examined the influence of different inventory control policies on the CLSC bullwhip effect. Using Laplace transforms, Zhou and Disney (2006) found that CLSCs with remanufacturing operations tend to experience a lower bullwhip effect than traditional supply chains without remanufacturing. In contrast, through a simulation study, Chatfield and Pritchard (2013) determined that permitting customer returns of unused products increases the bullwhip effect. Turrisi et al. (2013) examined the influence of reverse logistics on the bullwhip effect. They proposed a policy called R-APIOBPCS—a variant of the order-up-to policy for CLSCs— to mitigate the bullwhip effect in these systems. Hosoda et al. (2015) studied the value of advance notice of returns in reducing the bullwhip effect of CLSCs. They found that this value was largely dependent on lead time, random return yields and other reverse flow parameters. Cannella et al. (2016) investigated the behaviour of the CLSC bullwhip effect, identifying that reducing the remanufacturing lead time and promoting information transparency could mitigate this phenomenon. Ponte et al. (2020a) also studied the influence of information transparency on CLSC dynamics by deriving the order and inventory variance amplification ratios of four CLSCs with different information-sharing levels. Cannella et al. (2021) examined proportional controllers' impact on CLSC dynamics based on order-up-to policy. Giri and Glock (2022) investigated the bullwhip effect of a CLSC with manufacturing and remanufacturing operations that faced a price-dependent demand with an autoregressive moving average (ARMA) pricing process. They observed that the bullwhip effect of such a supply chain was related to the parameters of ARMA processes. Ponte et al.

(2022) explored the effect of batching on the bullwhip effect and service level of CLSCs. They found that this influence was not linear; the order and inventory variance amplification ratios were complex functions of the batch size that often define waveforms. Gao et al. (2022) investigated the bullwhip and inventory cost of an online CLSC. They compared the performance of the CLSC under different locations of the return inspection system, and optimise the return decisions for different cases.

Methodologically, the existing literature commonly applied three methods when studying CLSC dynamics. These are system dynamics simulation (e.g. Cannella et al., 2016), control theoretic models (e.g. Tang and Naim, 2004) and stochastic process models (Hosoda et al., 2015; Giri and Glock, 2022). Among these, system dynamics simulation seems the most frequently applied technique, especially when a system is non-linear or the analytical results are difficult to derive (e.g. Ponte et al., 2022; Cannella et al., 2021; Turrisi et a., 2013).

To summarise, the previous literature has adequate studies on the effects of several factors—such as remanufacturing lead times, return rates, information transparencies and inventory control policies—on the dynamics of CLSCs. Specifically, longer remanufacturing lead time can lead worse CLSC dynamics (e.g. Tang and Naim, 2004), while different levels of return rate and information transparency can pose opposite influence on bullwhip depending on the supply chain structure (e.g. Tang and Naim, 2004, Ponte et al., 2020, Zhou and Disney, 2006). Inventory control policies, if properly designed, can facilitate the reduction of bullwhip and thus the improvement of the CLSC dynamic performance (e.g. Cannella et al., 2021).

Although there are many factors studied in the previous literature, one of the important factors that studies have largely ignored is the effect of capacity constraints on CLSC bullwhip. Ignoring the influence of capacity constraints may not fully reflect the behaviour of many practical CLSCs that operate in a nonlinear capacitated settings (Georgiadis et al., 2006; Mohajeri and Fallah, 2016; Lin and Naim, 2019). It has been demonstrated that the capacity constraint policy plays a key role in influencing the dynamics of inventory systems (Lin and Naim, 2019; Dominguez et al. 2019). Relaxing such constraint may ignores oscillations generated internally by the system itself and make it difficult to fully explain the complex dynamics of real-world CLSCs.

2.2 Capacity constraints in closed-loop supply chains

Section 2.1 demonstrate the importance of a good dynamic performance of CLSC. The existing literature reveals dynamic performance of CLSCs may be strongly associated with capacity constraints (Vlachos et al., 2007). There are two types of constraints to consider in the reverse flow of CLSCs: return collection and production capacities (Georgiadis et al., 2006; Vlachos et al., 2007; Georgiadis and Athanasiou, 2013). The former is the capacity constraint on the collection of used products; the latter represents constraints on the recovery process (typically remanufacturing). For example, Georgiadis et al. (2006) and Vlachos et al. (2007) considered both return collection and remanufacturing capacity constraints in CLSCs. Using a system dynamics simulation, they each optimised dynamic capacity plans under different scenarios.

Although several CLSC studies have considered these capacity constraints (e.g. Zhalechian et al., 2016; Bice and Batun et al., 2021), very few papers examined their influence on the bullwhip effect. In this direction, only three papers have been identified. Adenso-Díaz et al. (2012) examined capacity constraints on the operations of recyclers (among many other factors), but the results showed that the different levels of constraints possess no statistical influence on the CLSC bullwhip effect. Dominguez et al. (2019) explored manufacturing and remanufacturing capacity constraints in CLSCs, finding that remanufacturing capacity constraints can present a bullwhip-dampening effect. Tombido et al. (2021) considered both return collection and remanufacturing capacities, and by comparing different scenarios, they examined how these capacity constraints affect the bullwhip effect depending on the various system parameters.

To summarise, although the previous literature has confirmed that capacity constraint is an important factor to influence CLSC performance and studied such an influence on the investment decisions, carbon emissions or logistics flows of the CLSC system (e.g. Vlachos et al., 2007; Mohammed et al., 2017; Bice and Batun et al., 2021), only the three studies reviewed above investigated the influence of capacity constraints on CLSC from a bullwhip perspective. In addition, only one paper considered the return collection capacity constraints explicitly, but the researchers focused on static constraints only (Tombido et al., 2021). Thisignored the fact that the capacity constraints of return collection may be changed over time due to uncertainties in the collection process, such as timing, quantity, and quality (Goltsos et al., 2019). For example, the return collection capacity in recycling sectors became unreliable and exhibited high levels of fluctuation driven by COVID-19 (Staub, 2021). Therefore, by reviewing previous literature, it shows there should be deeper investigation on the influence of stochastic rather than deterministic return collection capacity constraints on CLSC bullwhip, which justifies the theoretic and practical values of this paper.

2.3 Partial backlog in supply chains

In this paper, we also explore the PBRC phenomenon, which is a customer behaviour that is associated with SCCC. Partial backlogs in a forward supply chain generally refer to a situation in which, after experiencing stock-outs, only a fraction of unfulfilled customers are willing to wait until the product is available. In contrast, other unfulfilled customers are not willing to postpone their purchase, and therefore stock-outs will become lost sales (Hu et al., 2009).

There are multiple reasons for partial backlogs in real-world supply chains. For example, Chang and Dye (2001) indicated that a long waiting time is a main factor that triggers partial backlogs in supply chains. They showed that the backlog proportion is negatively related to the waiting time before order satisfaction. Lin (2013) argued that the attractiveness of products and the level of promotion determine the rate of partial backlog. Importantly, they concluded that the rate of partial backlog might be increased by investing in strengthening the factors that attract customers. Feng et al. (2018) revealed that, compared with assuming a full backlog or complete lost-sales setting when stock-out occurs, the assumption of partial backlog is more realistic. Adak and Mahapatra (2020) investigated the partial backlog phenomenon in multi-item supply systems where demand is dependent on multiple factors, such as advertising and reliability.

The existing literature has mainly examined partial backlogs related to customer demand for new products. However, we argue here that a similar phenomenon can occur in the reverse flow of materials, particularly in the return process of used products. When customers want to recycle or remanufacture used products, they may return them to collection facilities. However, when the product return collection capacity is constrained, and the used products cannot be collected instantly, customers may behave differently. Some customers will wait for future return collection, and will send the product to collection facilities at a later opportunity. This is known as a return collection backlog (Tombido et al., 2021). In contrast, other customers will not wait and will simply dispose of used products in other ways. In other words, uncollected returns that result from a limited return collection capacity will only be partially collected in the future.

In some industries, customers can take products they want to recycle to collection stations (Ahmadzadeh and Vahdani, 2017). In others, customers can book collection services online, and workers from collection stations will collect used products from customers' homes. However, unexpected events, such as bad weather or pandemic lockdown policies, can constrain the return collection capacity. For example, collection stations can be temporarily closed, or home collection services may be temporarily unavailable. In these cases, customers must keep used products on hand and wait for future collections. However, it is not likely that all customers unable to return products will be willing to wait. Some may consider disposing of the used products. Therefore, it is reasonable to argue that the phenomenon of PBRC is common.

To summarise, previous studies thoroughly examined the impacts of partial backlog rate in forward supply chains and confirm its impact on overall supply chain performance. This is because different partial backlog rate will determine the ordering policies, transportation plans, and the design of inventory control strategies (e.g. Lin et al., 2013; Feng et al., 2018). However, to the best of our knowledge, no research has examined the *partial backlog* in the CLSCs. The previous literature has either assumed that uncollected used products would be completely lost and disposed of (Vlachos et al., 2007), or that all customers would be willing to wait until they could return them (Tombido et al., 2021) in the CLSCs. Considering the importance of PBRC regarding its great economic and environmental significance, it is necessary to model and exam the dynamics of PBRC in CLSCs, Therefore, this paper will address this gap and contributes to the existing research.

2.4. Summary of research gaps

Table 1 summarises the most relevant previous literature and positions our paper within existing studies.

Table 1. Previous literature and positioning of the current paper

	Bullwhip in CLSCs	Return collection capacity constraints in CLSCs	Stochastic capacity constraints	Partial backlog in supply chain
Chang and Dye (2001)				✓
Tang and Naim (2004)	✓			
Georgiadis et al. (2006)		✓		

	Bullwhip in CLSCs	Return collection capacity constraints in CLSCs	Stochastic capacity constraints	Partial backlog in supply chain
Zanoni et al. (2006)	✓			
Zhou and Disney (2006)	✓			
Vlachos et al. (2007)		✓		
Hu et al. (2009)				✓
Georgiadis and Athanasiou (2010)		✓		
Adenso-Díaz et al. (2012)	✓			
Chatfield and Pritchard (2013)	✓			
Georgiadis and Athanasiou (2013)		✓		
Lin (2013)				✓
Turrisi et al. (2013)	✓			
Hosoda et al. (2015)	✓			
Cannella et al. (2016)	✓			
Zhalechian et al. (2016)		✓	✓	
Ahmadzadeh and Vahdani (2017)		✓	✓	
Mohammed et al. (2017)		✓	✓	
Feng et al. (2018)				✓
Dominguez et al. (2019)	✓			
Adak and Mahapatra (2020)				✓
Ponte et al. (2020a)	✓			
Bice and Batun (2021)		✓		
Cannella et al. (2021)	✓			

	Bullwhip in CLSCs	Return collection capacity constraints in CLSCs	Stochastic capacity constraints	Partial backlog in supply chain
Tombido et al. (2021)	✓	✓		
Gao et al. (2022)	✓			
Giri and Glock (2022)	✓			
Ponte et al. (2022)	✓			
This paper	✔	✔	✔	✔

From the Table 1, the research gaps can be summarised as follows. On the one hand, the existing CLSC bullwhip literature has not fully considered the effect of SCCC on the dynamic behaviour of CLSCs, but model constraints in the real-world collection process as a fixed value. On the other hand, no research has investigated the phenomenon of PBRC in the reverse flow of CLSCs. This phenomenon is associated with SCCC and is driven by customers who want to return used products behaving in different ways when they cannot do this because of capacity restrictions. Some may be willing to wait for the next opportunity to return the product (Tombido et al., 2021), while others may simply dispose of it (Georgiadis and Athanasiou, 2013). By filling these research gaps, we ensure that our model is more realistic and thus can offer a deeper understanding of how collection affects the bullwhip effect of CLSCs. We also provide valuable managerial insights on the capacity planning of collection centres to improve customer service and reduce supply chain costs.

3. Model

3.1 Preliminaries

In this section, we build a stylised model of CLSCs with SCCC and PBRC. The supply chain structures, operation processes, and information and material flows are largely based on previous studies (e.g. Dominguez et al., 2019; Georgiadis and Athanasiou, 2010; Georgiadis et al., 2006). They are visualised in Figure 1. In this system, mixed manufacturing–remanufacturing operations are assumed. This structure is commonly observed in different businesses, such as the spare parts industry (e.g. van der Laan and Teunter, 2006; Souza, 2013) and the printing industry (e.g. Zuidwijk et al. 2005; Zhou et al., 2017). As Figure 1 indicates, in this CLSC, retailers will receive newly manufactured and remanufactured products to replenish on-hand inventories from suppliers and remanufacturers, respectively. When customers in the market purchase retailer's products, the retailer will use on-hand inventory to satisfy customer demand. The quantity of new products delivered in each period is based on retailers' orders; retailers will consider the work-in-process (WIP) information of suppliers and remanufacturers simultaneously when making order-placement decisions (Ponte et al., 2021). In addition, the quantity of remanufactured products received is determined by the number of returned products first collected by the collection station and then processed by the remanufacturer in each period. The collection process is the key novelty in our modelling work. Specifically, after a consumption delay, customers will generate the used products to be collected by the collection station and delivered to the remanufacturer, but only a fraction of the returned products will be collected because of the station's SCCC. The remaining customers who fail to return products will either choose to wait for future collections as a result of PBRC or dispose of the used products.

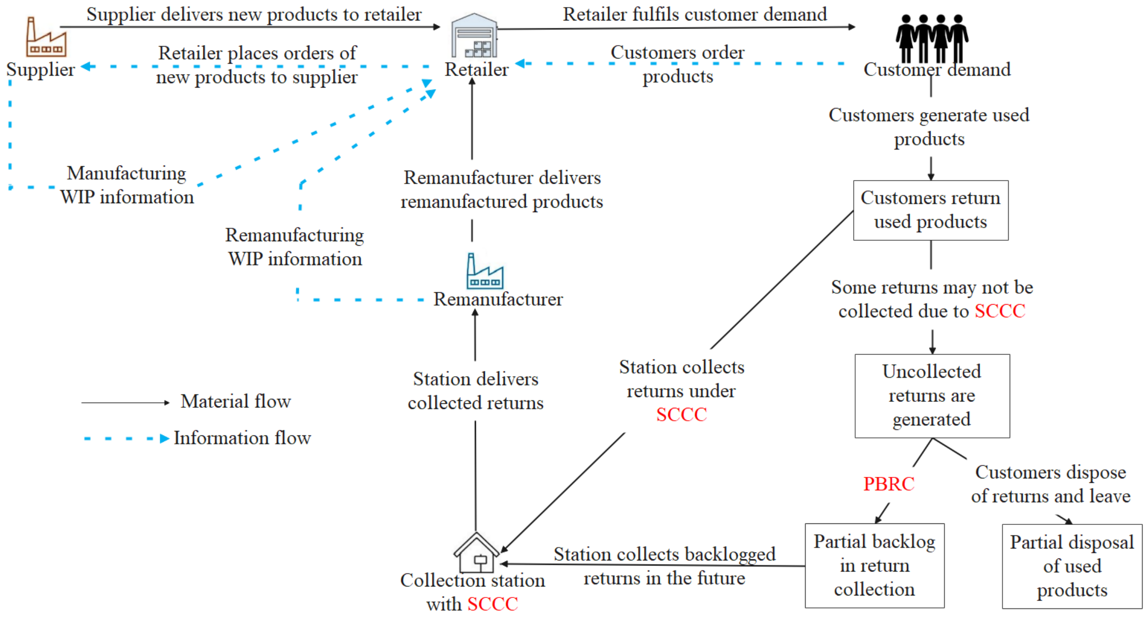

Figure 1 Caption: Stochastically capacitated closed-loop supply chains with partial backlog in the return collection

Figure 1 Alt Text: A CLSC model with customer, supplier, retailer, remanufacturer and collection station involved, where customers in this supply chain have PBRC when their returns are not collected because of SCCC

3.2 Assumptions

Before explaining the technical details in Section 3.3, we introduce several general assumptions made in our CLSC model, as follows:

- *Customer return process*: Following Zhou et al. (2017) and Ponte et al. (2020a), we assume that a fixed proportion of customers will attempt to return their products through collection stations after a consumption delay. However, some products will not be collected given limited return collection capacity. To reflect such uncertainty, we assume that this constraint is stochastic (Zhalechian et al., 2016). To embed the PBRC into our model, we assume that not all customers who fail to return used products are willing to wait for future return collection (see the technical details in Section 3.3).
- *Remanufacturing process*: The returned products collected at a collection station are assumed to be delivered to the remanufacturer for processing. Following Cannella et al. (2016), we assume that all collected returns can be remanufactured. Once completed, the remanufactured products are assumed to have the same properties and price as newly manufactured products; that is, remanufactured products are as good as new. In this fashion, both products can be used to fulfil customer demand (Tang and Naim, 2004). A perfect substitution of remanufactured and manufactured products is a common assumption for exploring the dynamics of CLSCs (e.g. Hosoda and Disney 2018; Ponte et al. 2019; Hosoda et al. 2020), as well as in other CLSC studies (e.g. van der Laan and Teunter, 2006; Atasu et al., 2013). Indeed, this is frequently observed, as with spare parts (e.g. van der Laan and Teunter, 2006) or toner cartridges (e.g. Nichols, 2014). Additionally, because we focus on the capacity constraint of the return collection process, we assume there are no capacity limitations in the remanufacturing process.
- *Manufacturing process:* The manufacturing process, which provides newly manufactured products to the retailer, operates according to the needs of the on-hand inventory. This is controlled through a periodic review replenishment policy, which also depends on the remanufacturing process. In line with previous research, we assume that the supplier always has enough capacity to manufacture all required products (Cannella et al., 2021; Lin et al., 2021).
- *Inventory process, customer demand fulfilment and retailer order placement:* the retailer's inventory capacity is assumed as infinite. The retailer will use on-hand inventory to fulfil customer demand, and unfulfilled demand will be fully backlogged (Tang and Naim, 2004). For retailer order placement, we assume a non-negative

ordering policy; this means that products cannot be returned from the retailer to the supplier (Wang et al., 2012).

3.3 Formulation

We develop our system dynamics model on the basis of previous studies of CLSC dynamics (e.g. Tang and Naim, 2004; Cannella et al., 2021). Using the model settings and assumptions described above, we present a causal loop diagram in Figure 2. System dynamics simulation has great advantage of modelling and exploring complex system structures including feedback loop, delay and nonlinearities (Sterman 2000). In particular, comparing other methods such as control theoretic and stochastic analysis, system dynamics simulations gain deeper understanding of system nonlinearities present in the supply chains. In our CLSC model, the nonlinearity is generated from two sources; namely, the stochastic capacity constraints of return collection, as well as PBRC. Either can make the analytical results of the system difficult to obtain. Therefore, compared with previous publications that use stochastic process models (Giri and Glock, 2022) or control theoretic models (Lin et al., 2021), we regard system dynamics as an appropriate option to effectively investigate the relationship between return collection and the bullwhip effect. We model the capacity constraints as a random variable in the system dynamics models and add the partial backlog property in the return process to make the model more realistic. Figure 2 provides an overview of our model by highlighting the relationship between the different variables and parameters. The causal relationship between uncollected customer returns and other factors, such as capacity, return rate and the percentage of partial backlog in the return process, is observable here. The details of this diagram will be explained in the following paragraphs of this section.

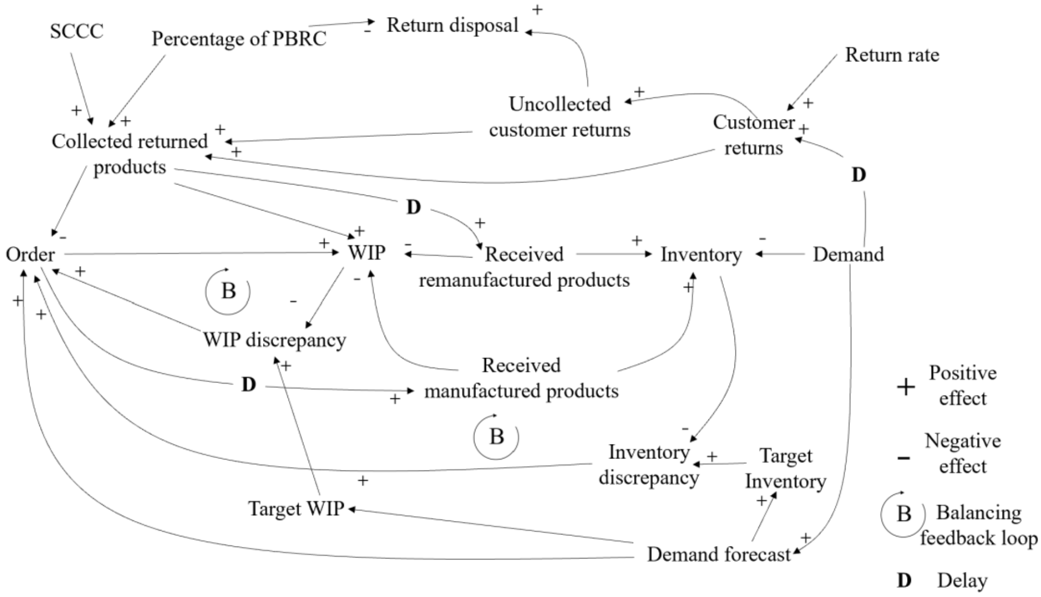

Figure 2 Caption: Causal loop diagram of closed-loop supply chains with collection dynamics considering stochastic capacity constraints of a collection station and partial backlog in return collection

Figure 2 Alt Text: A graph describing the causal relationships of variables related to CLSCs.

The notations of the model are listed in Table 2, and the sequences of the different activities in period t are described in Figure 3.

Table 2. Notations of the variables and parameters of the closed-loop supply chain model

Notation	Explanation
D_t	Customer demand in period t
PM_t	Received newly manufactured products in period t
RM_t	Received remanufactured products in period t
I_t	On-hand inventory in period t, after satisfying customer demand
R_t	Customer returns in period t
RC_t	The collected returned products in period t
WIP_t	WIP in period t
UC_t	Uncollected customer returns in period t
CC_t	The realisation of SCCC in period t
ε_t	Stochastic component of SCCC in period t

$\widehat{D}_t$	Demand forecasting in period t
TI_t	Target inventory level in period t
$TWIP_t$	Target WIP level in period t
O_t	Order placed in period t
μ	Mean of customer demand
σ	Standard deviation of customer demand
T_m	Manufacturing lead time
T_r	Remanufacturing lead time
L_c	Consumption lead time
k	Return rate
p	Percentage of PBRC
μ_{cc}	Mean value of SCCC
β	Volatility level of SCCC
CI	Capacity index
α	Exponential smoothing parameter
T_i	Inventory proportional controller
T_{wip}	WIP proportional controller

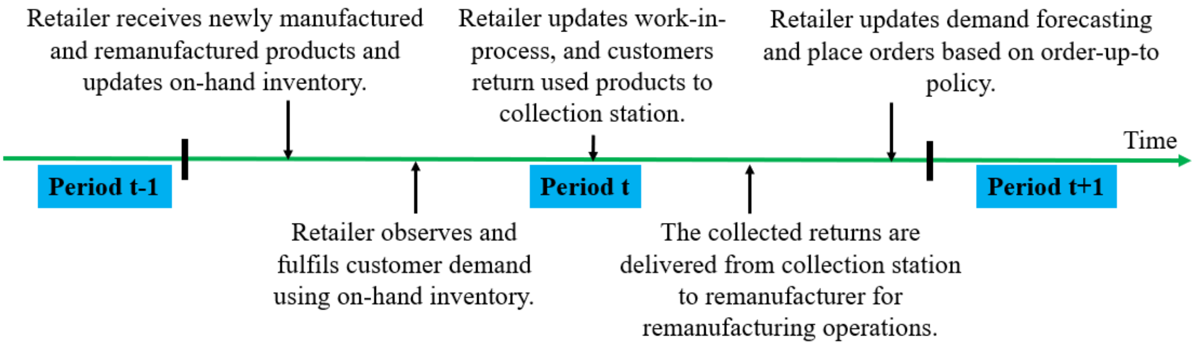

Figure 3 Caption: Sequences of activities in closed-loop supply chains

Figure 3 Alt Text: A graph describing the activities of closed-loop supply chains, including receiving products, fulfilling customer demand, collecting returns, update of demand forecasting and placing orders.

Specifically, in each period $t \in \{1,2,3, \ldots, T\}$, the customer demand for products is D_t, which is assumed to follow a normal distribution $D_t \sim N(\mu, \sigma^2)$ (Ponte et al. 2020a). For the retailer, as depicted in Figure 2, the in-flow of inventory consists of two sources, namely, manufactured and remanufactured products, while the out-flow of inventory is the customer demand in each period. This means that at the beginning of period t, the retailer will receive the newly manufactured and remanufactured products from the supplier—as well as the remanufacturer—to replenish its on-hand inventory. The on-hand inventory is then used to fulfil customer demand. We notate in period t the received manufactured products as PM_t, remanufactured products as RM_t and on-hand inventory after fulfilment as I_t; hence, for $t \in \{1,2,3, \dots T\}$, the following relationship holds:

$$I_t = I_{t-1} + PM_t + RM_t - D_t \quad (1)$$

To eliminate trivial cases, we set $I_0 = 0$, reflecting that the retailer is not open to working until Period 1.

We assume a constant lead time for manufacturing and remanufacturing, denoted by T_m and T_r, respectively. As illustrated in Figure 2, there will be a delay between a retailer placing an order and receiving manufactured products because the supplier needs time to complete the order. To model this relationship, PM_t is equal to the order placed from the retailer to the supplier $T_m + 1$ period ago (the one period here is the order reviewing period; see Cannella et al., 2021; Dejonckheere et al., 2003). Notating the order in period t as O_t, for $t \in \{1,2,3, \dots, T\}$ we have the following:

$$PM_t = O_{t-T_m-1} \quad (2)$$

To eliminate trivial cases, we set $PM_t = 0$ for all $t \leq T_m + 1$, reflecting that the retailer is not open to fulfilling customers and placing an order until Period 1.

In contrast, as observed in Figure 2, there will also be a delay between return reception and retailers receiving remanufactured products. To model this, RM_t is equal to the returns collected $T_r + 1$ period ago where the T_r is called the remanufacturing lead time. The one extra period here is consistent with the previous literature (Cannella et al., 2021), meaning that returned products (after collection in the current period) will not enter the remanufacturing process until the beginning of the next period. This reflects that the activities between return collection and remanufacturing, such as the counting and inspection of returned products, take time to complete. Additionally, this one extra period makes the notation of remanufacturing compatible with that of manufacturing processes. Denoting the returns collected in period t as RC_t, for $t \in \{1,2,3, \dots, T\}$ we have the following:

$$RM_t = RC_{t-T_r-1} \tag{3}$$

To eliminate trivial cases, we set $RM_t = 0$ for all $t \leq T_r + L_c + 1$, and set $RC_t = 0$ for all $t \leq L_c$ (see below for more details).

After receiving products from the supplier and remanufacturer and fulfilling customer demand, retailers update the WIP volume (WIP_t) to support their order decisions. Observed in Figure 2, the retailer has information on both manufacturing and remanufacturing activities (Dominguez et al., 2019; Lin et al., 2021), and for $t \in \{1,2,3,\dots,T\}$, the following relationship holds:

$$WIP_t = WIP_{t-1} + (O_{t-1} - O_{t-T_m-1}) + (RC_{t-1} - RC_{t-T_r-1}) \tag{4}$$

We set $WIP_0 = 0$ because the supplier has not received an order from a retailer until the end of first period. Equation 4 essentially indicates that the WIP in period t considers two elements. First, it includes all orders placed for the manufacturing lines but not delivered to the retailer. It also includes all the collected returns that have been pushed to the remanufacturing lines but not yet received by the retailer. T_m and T_r are the lead time for manufacturing and remanufacturing, although they may also represent the time spent on transporting new and remanufactured products, respectively. Because our model is rooted in a periodic review system, the WIP level is updated in every period, given that the relevant decision-making takes place at this frequency.

After the retailer updates WIP_t, the remanufacturer will collect the returned products. In each period, customers need to return used products to the collection station, and the station will deliver the collected returns to the remanufacturer. Consistently with previous studies (Zhou et al., 2017; Ponte et al., 2020a), the customer returns of products in period t, called R_t, are equal to a proportional demand L_c period ago, where L_c is the consumption lead time (Ponte et al., 2021). Therefore, for $t \in \{1,2,3,\dots,T\}$, we have:

$$R_t = k \cdot D_{t-L_c} \tag{5}$$

R_t is set as 0 when $t \leq L_c$, to eliminate trivial cases, since there are no customers finishing consumption of the products. This leads to the above setting in Equation 4 that for $t \leq L_c + T_r + 1$, RM_t is set as 0 because no remanufactured products have been completed. Here, k is the return rate, and $0 \leq k \leq 1$. The return rate is assumed as a constant, which is consistent with previous literature (e.g. Tang and Naim, 2004; Ponte et al., 2020a).

However, because a collection station is capacitated in its collection capacity, it is possible that not all returned products in period t will be collected for remanufacturing (Tombido et al., 2021). Therefore, PBRC leads to an assumption that some uncollected returns will be accumulated for the next period if customers are willing to wait, while other returns will be disposed of if customers cannot wait. To model the property of PBRC, we notate the uncollected products in period $t-1$ as UC_{t-1} and the percentage of partial backlog in the return collection as p $(0 \leq p \leq 1)$. Thus, p is the percentage of PBRC, representing the percentage of customers who have uncollected products in period $t-1$ and will wait to return products in period t. This means that a portion of $1-p$ impatient customers with uncollected products in period $t-1$ will dispose of returns. Linking this to practice, p can represent the attributes of customers with uncollected returns. For example, p can mean the average degree of customer environmental awareness. Previous empirical research indicates that customers with a higher degree of environmental awareness are more likely to return products (Ramayah et al., 2012). Therefore, it can be reasonably inferred that the higher the average degree of customer environmental awareness, the higher the portion of customers (i.e. higher p) who are willing to wait for future collection will be. Additionally, as reflected in previous research (e.g. Jena et al., 2017), p can measure the incentives (e.g. money, coupon) that a collection station offers to customers returning products, so a higher p can mean stronger incentives which stimulate a higher portion of customers to wait for return collection. From the property of p, we further notate that the capacity constraint of a collection station in period t is CC_t and the following relationship holds for $t \in \{1,2,3,\dots,T\}$:

$$RC_t = min\{CC_t, p \cdot UC_{t-1} + R_t\} \tag{6}$$

$$UC_t = p \cdot UC_{t-1} + R_t - RC_t \tag{7}$$

To eliminate trivial cases, we set $UC_0 = 0$, reflecting that there are no returns uncollected for periods when customers have not generated returns.

Essentially, Equations 6 and 7 reflect two scenarios. On the one hand, if in period t the sum of accumulated previous customer returns (i.e. $p \cdot UC_{t-1}$) and current customer returns (i.e. R_t) is not greater than the capacity constraint of collection station (i.e. CC_t), then all returns will be collected, leading to the relationship that $RC_t = p \cdot UC_{t-1} + R_t$. Here, UC_t is essentially equal to zero, meaning that in period t, no returns are uncollected. On the other hand, if in period t the sum of accumulated previous customer returns (i.e. $p \cdot UC_{t-1}$) and current customer returns (i.e. R_t) is greater than CC_t, the returns collected are only constrained to CC_t. This results in a positive UC_t, indicating that some returns will remain uncollected.

It can be observed the PBRC modelled by Equations 6 and 7 is essentially a first-order relationship. This reflects that a larger volume of the total uncollected returns will lead to a greater disposal of used products in each period. This is justifiable because it suggests that a longer waiting time will lead to a higher probability of lost returns, which aligns with the literature on partial backlog (e.g. Lin, 2013), as well as industrial practice. Moreover, for CC_t in Equation 6, extending the literature (Dominguez et al., 2019; Tombido et al., 2021), we model it as a stochastic, rather than deterministic, value to capture the uncertainty of collection capacity (Zhalechian et al., 2016; Ahmadzadeh and Vahdani, 2017). We assume CC_t is the realisation of random variable, thereby SCCC, and for $t \in \{1,2,3, \dots, T\}$:

$$CC_t = \mu_{cc} + \varepsilon_t \tag{8}$$

where μ_{cc} is the mean value of CC_t, while ε_t is a random variable with a mean equal to 0 (we model ε_t in the next paragraph). To quantify μ_{cc}, we adopt Dominguez et al.'s (2019) and Zhao et al.'s (2002) approach, and define a capacity index (CI). Specifically, CI is assumed to be equal to μ_{cc} over the mean of the product return. In the current paper, because the mean value of customer demand is μ and the return rate is k, the mean value of the product return is $\mu \cdot k$, leading to the CI being equal to $\frac{\mu_{cc}}{\mu k}$. Therefore, for a given CI, $\mu_{cc} = \mu \cdot k \cdot CI$. From its mathematical expression, a lower CI means a tighter capacity constraint, while a higher CI means a looser capacity constraint. In practice, a higher CI represents the scenario where the company has higher spare capacity, including, for instance, a higher level of workforce, a larger storage space, a longer working hour and/or a higher transportation capacity of the return collection station (Katami et al., 2015; Tombido et al., 2022). Additionally, we emphasise that CI should always be greater than 1, meaning that the mean value of SCCC should be larger than the mean of the returned cores; otherwise, the system can be non-convergent (Dominguez et al., 2019).

Further, to model the stochastic element of SCCC, ε_t is assumed to follow a uniform distribution (Zhalechian et al., 2016; Ahmadzadeh and Vahdani, 2017; Wang et al., 2010). To measure the stochasticity of ε_t, we assume $\varepsilon_t \sim U(-\beta \cdot \mu_{cc}, \beta \cdot \mu_{cc})$, where $0 \le \beta \le 1$. Here, extending the literature, we define β as the volatility level of SCCC. From its formulation, a higher β indicates a more volatile SCCC. If $\beta = 0$, the assumption of capacity constraints returns to that noted by Dominguez et al. (2019) and Tombido et al. (2021). In practice, β indicates the degree of fluctuations of SCCC (Pishvaee et al., 2011). It considers the probability and severity of the disruptions that affect collection centres, including natural disasters, human-induced disasters, political crises, and epidemics and pandemics, among other things. In this sense, β can also capture some influences on capacity caused by the COVID-19 pandemic. For instance, employees of collection stations were asked to undergo quarantine and leave work when they caught the virus, which may have led to a change in capacity. However, we note that β might also be influenced by internal factors, such as strikes or the hiring and firing of staff.

At the end of each period, retailers must update their demand forecast (i.e. $\widehat{D}_t$) for the future and place an order with suppliers. Simple exponential smoothing is selected as the forecasting method; this a popular method that does not require significant real data storage for forecasting (Disney et al. 2000; Cannella et al. 2016). Also, unlike other methods such as ARIMA, which is very sensitive to parameter selection, exponential smoothing is a robust method (Udenio et al., 2022). Its simplicity, intuition, small computational effort and ease of application are well recognised in the literature (Disney et al. 2006; Li et al. 2014).

$$\widehat{D}_t = \alpha \cdot D_t + (1 - \alpha) \cdot \widehat{D}_{t-1} \tag{9}$$

α is the exponential smoothing parameter (Syntetos et al., 2011), and we have $t \in \{1,2,3, \dots, T\}$. Following Potter and Lalwani (2008), we set $\widehat{D}_0 = \mu$ to initiate forecasting, as it can effectively eliminate possible initialisation bias (Law, 2015).

According to I_t, WIP_t and $\widehat{D}_t$, retailers will place their orders with suppliers according to the rule of the automated pipeline, various inventory and order-based production systems (APVIOBPCS) (Lin et al., 2017; Lin et al., 2020):

$$O_t = \max\{0, \left(\widehat{D}_t - RC_{t-T_r-1}\right) + \frac{TI_t - I_t}{T_i} + \frac{TWIP_t - WIP_t}{T_{wip}}\} \tag{10}$$

In Equation 10, TI_t is the safety stock inventory and $TWIP_t$ is the targeted WIP level. T_i and T_{wip} are two proportional controllers for the gaps of inventory and WIP (Dejonckheere et al., 2004). An explanation for Equation 10, according to Zhou et al., (2017) and Cannella et al. (2019), is that the order quantity is equal to three components. The first component, $\widehat{D}_t -$

RC_{t-T_r-1}, is the difference between forecasted demand and the remanufactured products received. The second (i.e. $\frac{TI_t - I_t}{T_i}$) and third components (i.e. $\frac{TWIP_t - WIP_t}{T_{wip}}$) are the proportional discrepancy between target inventory and actual inventory, as well as the proportional discrepancy between target WIP and actual WIP, respectively. We refer interested readers to Zhou et al (2017) and Sterman (1989) for a detailed justification and explanation of the suitability of adopting this ordering rule. In line with Dejonckheere et al. (2003; 2004), the safety stock inventory is set as the forecasted demand. $TWIP_t$ is determined by forecasted demand during manufacturing and remanufacturing lead times (Tang and Naim, 2004):

$$TI_t = \widehat{D}_t \tag{11}$$

$$TWIP_t = [(1-k) \cdot T_m + k \cdot T_r] \cdot \widehat{D}_t \tag{12}$$

As reflected in Figure 2, the ordering rule receives negative feedback from I_t and WIP_t, leading to two balanced loops. APVIOBPCS generalises the well-known proportional order-up-to policy, which simplifies to the traditional order-up-to policy when $T_i = T_{wip} = 1$. Both policies are widely adopted by industry (Disney et al., 2021). For Equations 10, 11 and 12, we have $t \in \{1,2,3, \dots, T\}$. According to the above settings from Equations 1 to 7, the trivial cases of state variables (e.g. RC_{t-T_r-1}) in Equations 10 to 12 have already been eliminated.

3.4 Experimental design

In this section, we explain and justify the experimental design we have developed. The descriptions of the performance measures, experimental factors and fixed parameters are presented in Table 3.

Table 3. Experimental design

Performance Measures	Values
OVA: order variance amplification ratio	
IVA: inventory variance amplification ratio	
Experimental factors	
k: return rate	{0, 0.4, 0.7}
CI: capacity index	{1.1, 2.1, 3.1}
β: volatility level of SCCC	{0, 0.2, 0.4}

p: percentage of PBRC	{0, 50%, 100%}
Fixed Parameters	
μ: mean value of customer demand	100
σ: standard deviation of customer demand	10
L_c: consumption lead time	32
T_m: supplier production lead time	8
T_r: remanufacturing lead time	4
T_i: inventory proportional controller	8
T_{wip}: WIP proportional controller	8
α: exponential smoothing parameter	0.2

First, the order variance amplification (OVA) ratio and inventory variance amplification (IVA) ratio are adopted as the key performance metrics of our CLSC system. These two measures can indicate a system bullwhip effect (Huang et al., 2021; Turrisi et al., 2013; Ponte et al., 2020b), which directly links the cost efficiency and operations performance of the supply chain (Cannella et al., 2021; Chen and Disney, 2007). Specifically, OVA is defined as the variance of a retailer's order over the variance of the retailer's demand. IVA is equal to the variance of the retailer's finished good inventory over the variance of the retailer's demand (Zhou and Disney, 2006; Cannella et al., 2018):

$$OVA = \frac{var(O_t)}{var(D_t)} \tag{13}$$

$$IVA = \frac{var(I_t)}{var(D_t)} \tag{14}$$

Second, from the research question we posed in the introduction, we consider the influence of four experimental factors that are related to the collection process: capacity index (CI), volatility level of SCCC (β), the percentage of PBRC (p), and return rate (k). For CI, three levels are considered: {1.1, 2.1, 3.1}, which a higher CI means a looser capacity constraint (Dominguez et al. 2019). Setting the value of CI greater than 1 is of both theoretic and practical implications. Specifically, assuming CI greater than 1 can theoretically guarantees a stable system. Also, CI should be greater than 1 to fit the practical supply chains that the utilisation rate of capacity is less than 100% (Zhao et al. 2002; Lau et al., 2008). The minimum CI = 1.1 is chosen because it is a good value to approximate the situation that the system operates closed to its maximum capacity (Dominguez et al., 2019). Also, by following Dominguez et al. (2019), maximum *CI* =3.1 is determined to represent the scenario where the system has sufficient spare capacity. We also incorporate *CI*=2.1 as the middle value between 1.1 and 3.1 to obtain deep insights about how the change of CI may impact on the system dynamics performance. For the return rate, we use three levels: $\{0, 0.4, 0.7\}$, following Cannella et al. (2016). Here, we investigate a traditional forward supply chain without collection and remanufacturing ($k = 0$) along with a CLSC with a considerable volume of returns ($k = 0.4$) and a highly circular CLSC ($k = 0.7$). Considering a wide parameter space allows us to study the implications of CLSCs with different degrees of maturity.

For the volatility levels of SCCC, β, three levels are adopted: $\{0, 0.2, 0.4\}$. A higher β represents a more volatile constraint. When $\beta = 0$, this means that the remanufacturer has constant return collection capacity constraints, making our model return to the assumptions stated in Tombido et al. (2021). Furthermore, a stochastic collection station capacity of $\pm 20\%$ fluctuation around the mean capacity is assumed, in line with Mohammed et al. (2017) and Ahmadzadeh and Vahdani (2017). Note that we double the magnitude of fluctuation and adopt $\beta = 0.4$ to ensure that our model is more realistic in current post-pandemic business circumstances. The operations environment after COVID-19 has become more uncertain and unstable, and this means that stronger fluctuations in collection station operations are also likely. Finally, for the percentage of PBRC, three levels are assumed: $\{0\%, 50\%, 100\%\}$. Here, $p = 0$ means that it is possible that customers can dispose of all uncollected returns (Vlachos et al., 2007; Georgiadis et al., 2006). Conversely, customers whose returns are not collected are all willing to wait for future collection, meaning that $p = 100\%$ (Tombido et al., 2021). As both cases can be witnessed in practice, we thus adopt $p = 0$ and 100%, respectively. Also, to capture the properties of a partial backlog in the return collection, we further assume that $p = 50\%$, which is in the middle point of $p = 0$ and 100% to make our model fit practice.

Finally, for simulation parameters, following Tang and Naim (2004), Zhou et al. (2017) and Cannella et al. (2016), L_c is assumed as 32 periods, T_M as eight periods, T_R as four periods, and T_i and T_{wip} as eight. According to Dejonckheere et al. (2004), customer demand is assumed as $D_t \sim N(100{,}10^2)$, which means that $\mu = 100$ and $\sigma = 10$. For demand forecasting, α is equal to 0.2, which is consistent with Syntetos et al. (2011). We perform full factorial experiments using computer simulation in R programming language. Because we have four experimental factors, and each of these has three levels, the total number of experiments is $3^4 = 81$. To mitigate the effect of the randomness of our experiments, we conduct five replications for each, yielding $81 * 5 = 405$ simulation runs in total. For each run, 100,000 periods are simulated, with the first 20,000 as the 'warm-up' periods to fully eliminate possible initialisation bias. Analysis of variance (ANOVA) is used to analyse the simulation results (Cannella et al., 2021). The assumptions of homogeneity and normality are reviewed using Levene's test and the Shapiro-Wilk test. No violation of either is detected, which illustrates that the ANOVA results are valid (Huang et al., 2021).

4. Analysis of results

The ANOVA results for OVA and IVA are presented in Table 4, which indicates that all experimental factors and their interactions significantly influence both OVA and IVA at a 99% confidence level. On the one hand, the four main effects of the experimental factors are all statistically significant. As suggested by their F-value (Cannella et al., 2018), of the four factors, factor k (i.e. return rate) can have the most significant influence on OVA and IVA, followed by β (i.e. volatility level of SCCC), while p (i.e. the percentage of PBRC) has the least significant effect on both metrics. On the other hand, for interaction effects, on average the first-order interaction effects can have a more significant influence on OVA and IVA than higher order interactions. Among all the interaction effects, Table 4 shows that the interaction between β and CI can have the most significant influence on OVA and IVA. This section will analyse the main and interaction effects.

Table 4. Analysis of variance results

	OVA			**IVA**		
Experimental Factor	Df	F-value	P-value	Df	F-value	P-value
β	2	33849	< 0.001	2	427.54	< 0.001
k	2	405846	< 0.001	2	7194.32	< 0.001
p	2	5485	< 0.001	2	87.41	< 0.001
CI	2	13796	< 0.001	2	112.69	< 0.001
$\beta \cdot k$	4	14095	< 0.001	4	182.41	< 0.001
$\beta \cdot p$	4	3636	< 0.001	4	40.42	< 0.001
$k \cdot p$	4	2203	< 0.001	4	45.91	< 0.001
$\beta \cdot CI$	4	33729	< 0.001	4	380.2	< 0.001
$k \cdot CI$	4	5608	< 0.001	4	52.98	< 0.001
$p \cdot CI$	4	5732	< 0.001	4	118.62	< 0.001
$\beta \cdot k \cdot p$	8	1364	< 0.001	8	16.28	< 0.001
$\beta \cdot k \cdot CI$	8	14161	< 0.001	8	179.9	< 0.001

$\beta \cdot p \cdot CI$	8	3646	< 0.001	8	31.48	< 0.001
$k \cdot p \cdot CI$	8	2160	< 0.001	8	44.24	< 0.001
$\beta \cdot k \cdot p \cdot CI$	16	1369	< 0.001	16	15.52	< 0.001

4.1 Main effects

Figure 4 provides a general view of the effects of four experimental factors—CI, β and p and k—on OVA and IVA.

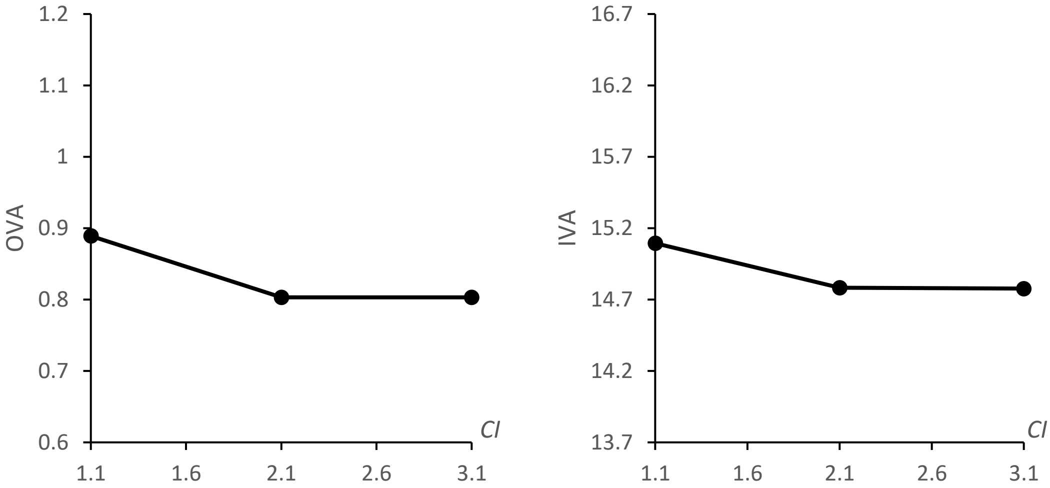

Figure 4a. Effects of CI on order and inventory variance amplification

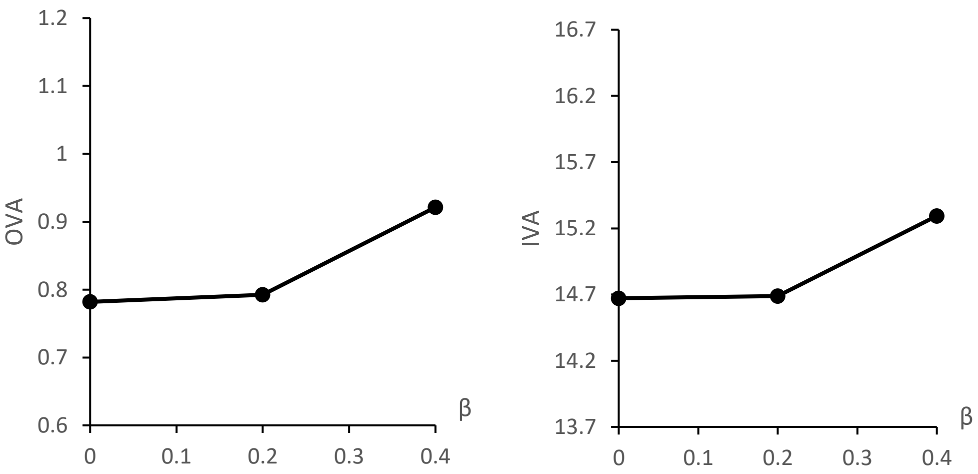

Figure 4b. Effects of β on order and inventory variance amplification

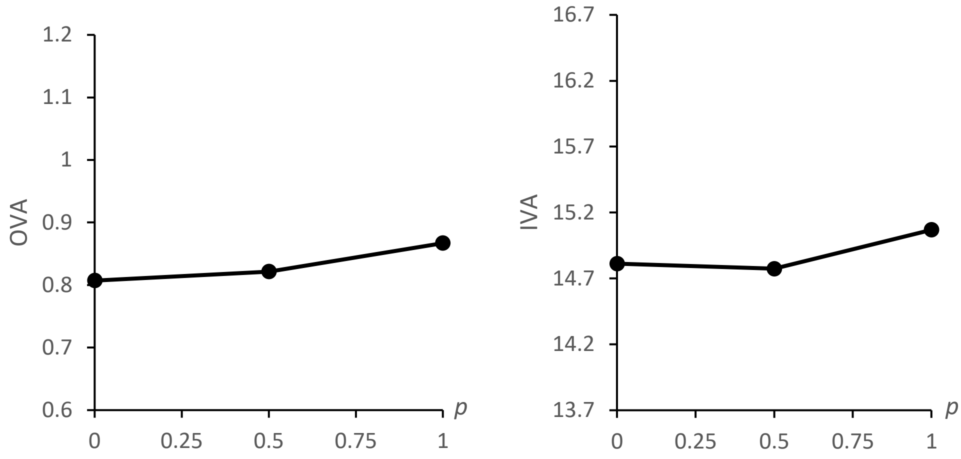

Figure 4c. Effects of p on order and inventory variance amplification

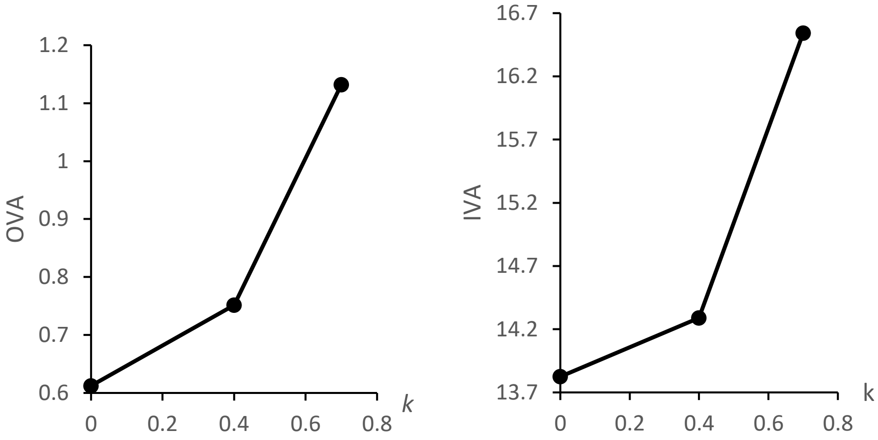

Figure 4d. Effects of k on order and inventory variance amplification

Figure 4 Caption: Main effects of the experimental factors on order and inventory variance amplification

Figure 4 Alt Text: 4 graphs examining the main effects of CI, β, p and k on order variance amplification ratio and inventory variance amplification ratio, respectively

First, Figure 4a presents the influence of CI on OVA and IVA. It can be observed that when CI is low (i.e. $CI = 1.1$), the increase of CI from 1.1 to 2.1 can lead to a reduction in both OVA and IVA. Specifically, the percentage of OVA reduction is 9.7%, while the percentage of IVA reduction is 2.1%. After that, when $CI = 2.1$, the increase of CI to 3.1 has a limited effect on both OVA and IVA because the difference of both measures between the two scenarios is less than 0.05%. This means that expanding the level of capacity in return collection can more effectively reduce the order and inventory variance amplification when the capacity constraint is tight. However, capacity expansion may bring a limited improvement to system dynamics performance if the constraint is loose. These findings contrast with those in the literature (e.g. Dominguez et al., 2019; Ponte et al., 2017) which find that production-based capacity constraints, such as remanufacturing capacity constraints, may act as a 'filter' to reduce order variance while simultaneously increasing inventory variance. This can be due to the phenomenon of PBRC, where the returned product can be accumulated for the next period. Our findings show that supply chain managers should treat production and return collection capacities in different ways by choosing appropriate policies (e.g. capacity expansion or capacity limitation) for improving system dynamics performance.

In addition, Figure 4b presents the effect of β on OVA and IVA. It can be observed that when β is low (i.e. $\beta = 0$), the increase of β from 0 to 0.2 results in a relatively small increase of OVA (1.3%) but has little effect on IVA, with a difference less than 0.2%. After that, when β is increased from 0.2 to 0.4, a much more significant increase in OVA and IVA can be identified, with the percentage of increase 16.3% and 4.1%, respectively. This means that a highly volatile SCCC damages the dynamic performance of CLSCs. Our findings not only support the literature (e.g. Hosoda et al., 2015) that suggests unstable reverse logistics and remanufacturing operations may have negative effects on the system, but also highlight the effect of volatility of SCCC on system dynamics performance and the necessity of stabilising return collection processes.

Figure 4c depicts the effect of p on OVA and IVA. It suggests that when p is low (i.e. $p = 0$), the increase of p from 0 to 50% only brings a relatively small increase (1.8%) on OVA, and has little effect on IVA with a difference less than 0.3%. However, when p is increased from 50% to 100%, this can more significantly increase both measures, with a 5.5% increase in OVA and a 2% increase in IVA. Finally, in Figure 4d, the effects of the return rate (i.e. k) on supply chain bullwhip are visualised. An increase in the return rate k leads to an increase of both OVA and IVA. Numerically, an increase of k from 0 to 0.4 brings a 22.7% increase in OVA and a 3.4% increase in IVA, while an increase of k from 0.4 to 0.7 leads to a 50.6% increase in OVA and a 15.8% increase on IVA. This result is consistent with the literature. For example, in their first two analytical models, Ponte et al. (2020a) found that the OVA and IVA of CLSCs are increasing functions of k. Hosoda et al. (2015) and Hosoda and Disney (2018) also found that the order and inventory variance of CLSCs will be higher with an increase of average product return. Thus, companies may have incentives to consider not remanufacturing all returned products. It should be noted that our results are different from other studies that determine an increase of k can decrease OVA (e.g. Tang and Naim, 2004; Zhou and Disney, 2006). An explanation for this may be that our CLSC system structure differs from these studies, and we consider PBRC and capacity stochasticity. To further discuss how k can increase OVA and IVA, we conducted a thorough sensitivity analysis (Section 4.3) by adjusting the CLSCs' structure parameters under the PBRC and SCCC.

4.2 Interaction effect

Consistent with the literature (e.g. Dominguez et al., 2019; Huang et al., 2021), we only analyse the first-order interaction effects in this section because these are highly interpretable and enable us to obtain valuable insights. Compared with previous literature (Dominguez et al., 2019; Tombido et al., 2021; Adenso-Díaz et al., 2012), the newly explored factors here are β and p. We focus on analysing those interaction effects containing β and p. These effects include $\beta \cdot p$, $\beta \cdot k$, $\beta \cdot CI$, $p \cdot k$, and $p \cdot CI$.

First, we consider the interaction effect between β and p. In Figure 5, the $\beta \cdot p$ interaction effects are visualised, with similar patterns for OVA and IVA observed. Specifically, when the β is small or moderate (i.e. $\beta = 0$ or 0.2), the different p has a similar influence on both OVA and IVA. However, when β is large (i.e. $\beta = 0.4$), increasing p results in a significant increase in OVA and IVA. This means that when the SCCC is highly volatile and unstable, the increase of the percentage of PBRC can more strongly lead to a rise of the CLSC bullwhip effect.

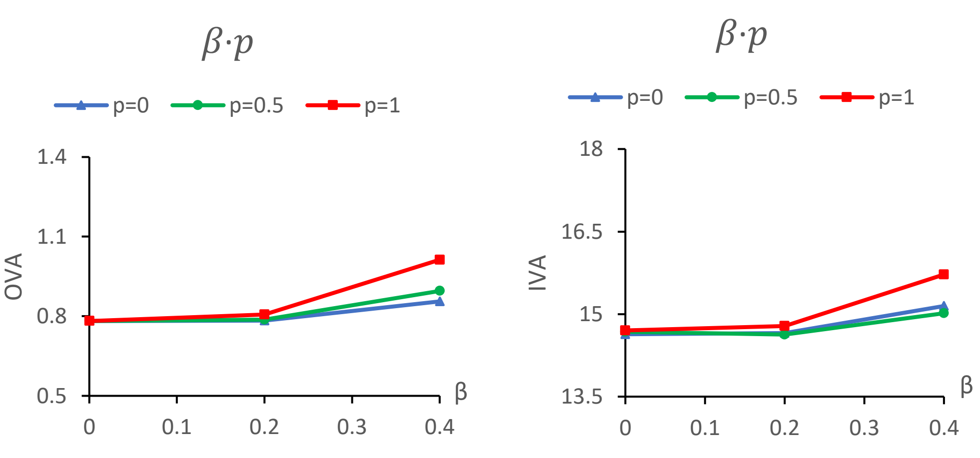

Figure 5 Caption: Interaction effect between β and p

Figure 5 Alt Text: A graph examining the interaction effect between different levels of β and p

Figure 6 visualises the interaction effects between β and k, and between β and CI, on OVA and IVA. On the one hand, a higher k can always lead to an increase in both OVA and IVA, especially when β is high. Specifically, although an increase of k can lead to an increase of both measures when β is 0 and 0.2, this effect from k looks stronger when β is 0.4. This means that when the volatility of SCCC is high, the return rate plays a more important role in influencing supply chain dynamics than when low SCCC volatility is present. On the other hand, the interaction effects between β and CI on OVA and IVA present a non-linear pattern. When CI is 2.1 and 3.1, β poses little influence on both measures. However, when CI is 1.1, in which case the capacity is quite tight, the increase of β can significantly increase OVA and IVA when β is moderate or high (i.e. $\beta = 0.2$ or $\beta = 0.4$). This suggests that companies should focus on the effect of an increasing β on dynamic performance reduction when the capacity constraint of return collection is tight.

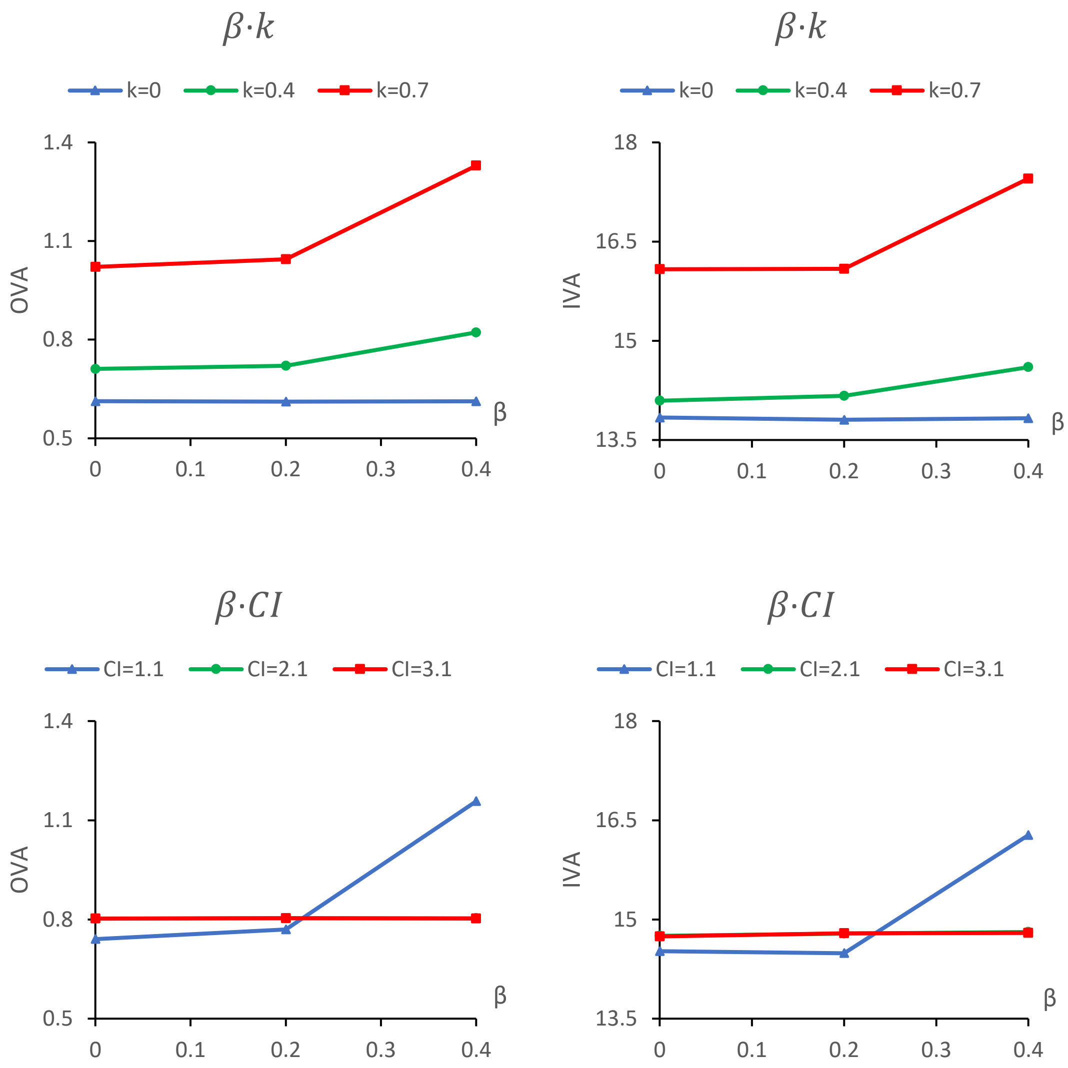

Figure 6 Caption: Interaction effect between β ***and*** k ***as well as*** β ***and*** CI

Figure 6 Alt Text: A graph examining the interaction effect between different levels of β *and* k *as well as between different levels of* β *and* CI

Finally, in Figure 7, the interaction effects between p and k, as well as p and CI, are presented. The interaction effects between p and k on OVA and IVA share similar patterns, and the increase of k can lead to a slightly stronger increase of both OVA and IVA when p is large (i.e. $p = 1$). In addition, the interaction effects between p and CI on OVA and IVA show that when CI is not very low (i.e. CI is 2.1 or 3.1), which means the capacity constraint of return collection is not too tight, different values of p essentially have a similar effect on both performance measures. When CI is low (i.e. CI=1.1), however, p has a positive influence on OVA, while an increase of p can lead to a significant increase in IVA when the value of p changes from 0.5 to 1.

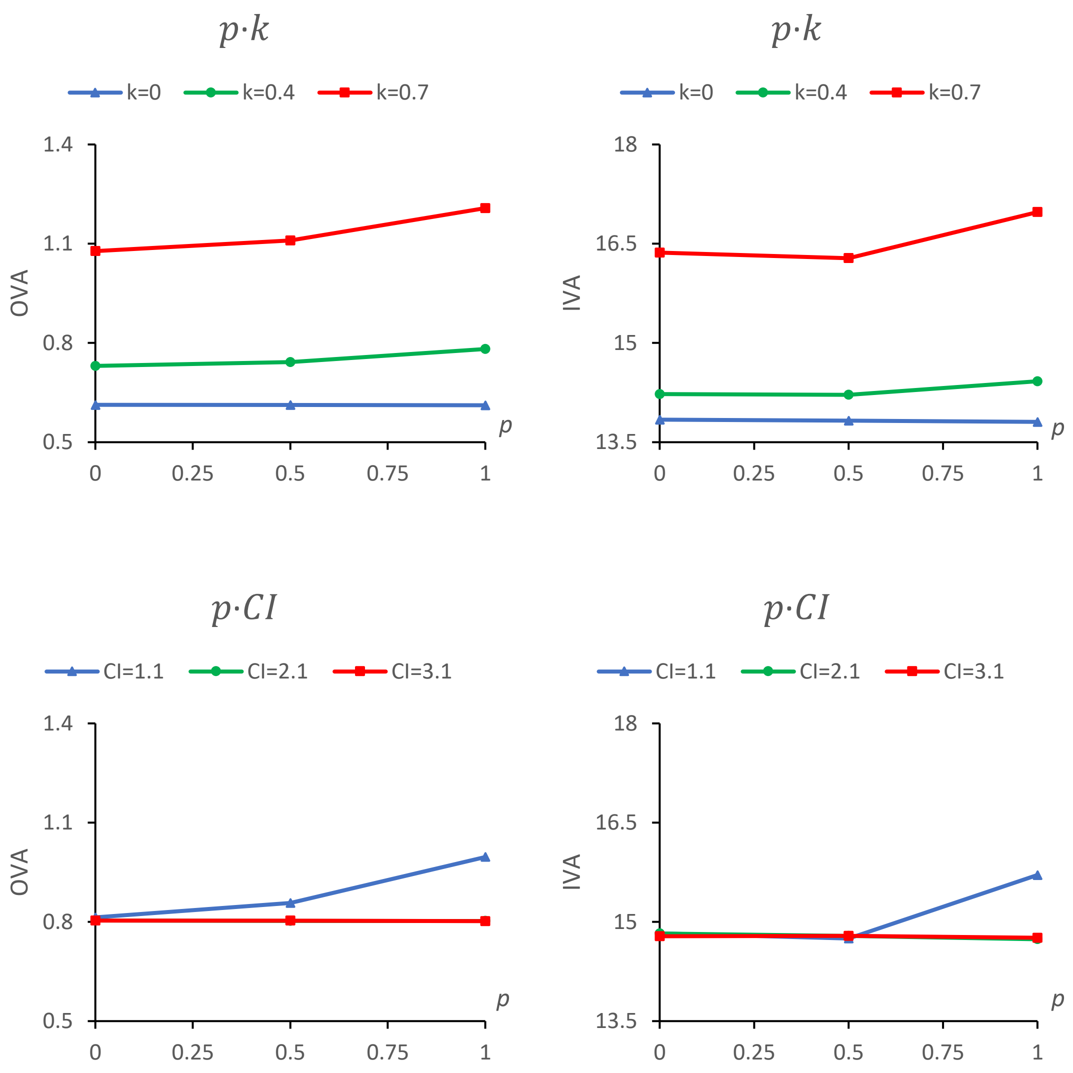

Figure 7 Caption: Interaction effects between p ***and*** k ***as well as*** p ***and*** CI

Figure 7 Alt Text: A graph examining the interaction effect between different levels of p *and* k *as well as between different levels of* p *and* CI

4.3 Sensitivity analysis

To test the robustness of the simulation results, we perform a systematic sensitivity analysis by altering different CLSC system parameters. Table 5 illustrates the system parameter settings adopted for sensitivity analysis, here following Turrisi et al. (2013), Cannella et al. (2016), Zhou et al. (2017), Cannella et al. (2019) and Lin et al. (2021). Overall, our sensitivity analysis indicates that the simulation results are generally robust to the change in system parameters, including manufacturing (T_m), remanufacturing lead time (T_r), inventory proportional controller (T_i) and WIP proportional controller (T_{wip}). However, the results may be sensitive to the change in the standard deviation of customer demand (σ) under certain situations.

Table 5. Sensitivity analysis

	Value in the Original Simulation	Values Adopted in Sensitivity Analysis
σ	10	5, 15, 20
T_r	4	2,6, 8
T_i and T_{wip}	8	4,12,16
T_m	8	4,12,16

4.3.1 Sensitivity analysis of σ

Following Cannella et al. (2016), Cannella et al. (2019) and Dejonckheere et al. (2004), we perform the sensitivity analysis using $\sigma = 5, 10, 15, 20$. Figure 8 reports the effect of demand standard deviation on OVA and IVA under different CI, β, p, and k. Here, the influences of k and β on OVA and IVA are generally robust under different values of σ, although the influence of CI is sensitive to a change of σ. In addition, the influence of p on both measures is robust under different σ except when σ is very low (i.e. $\sigma = 5$).

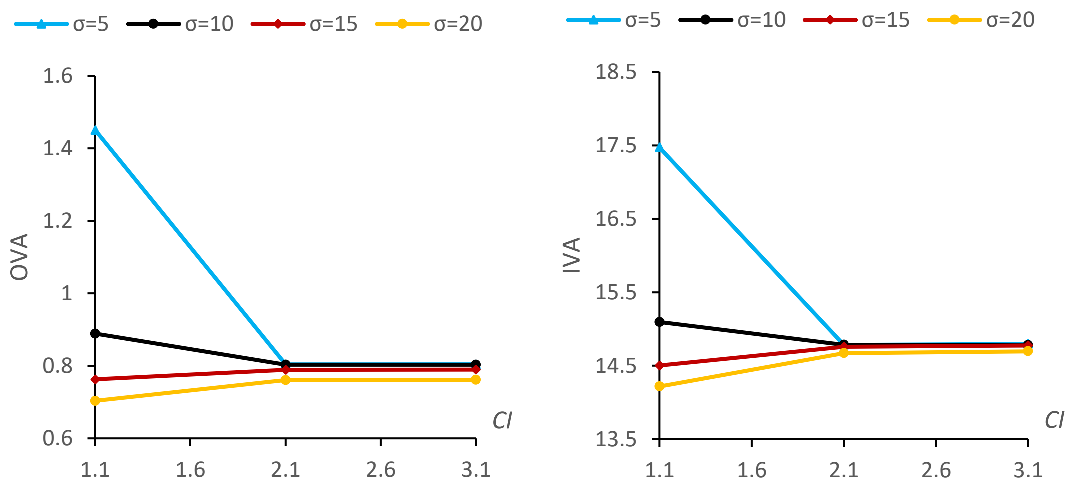

Figure 8a. The effect of CI under different σ

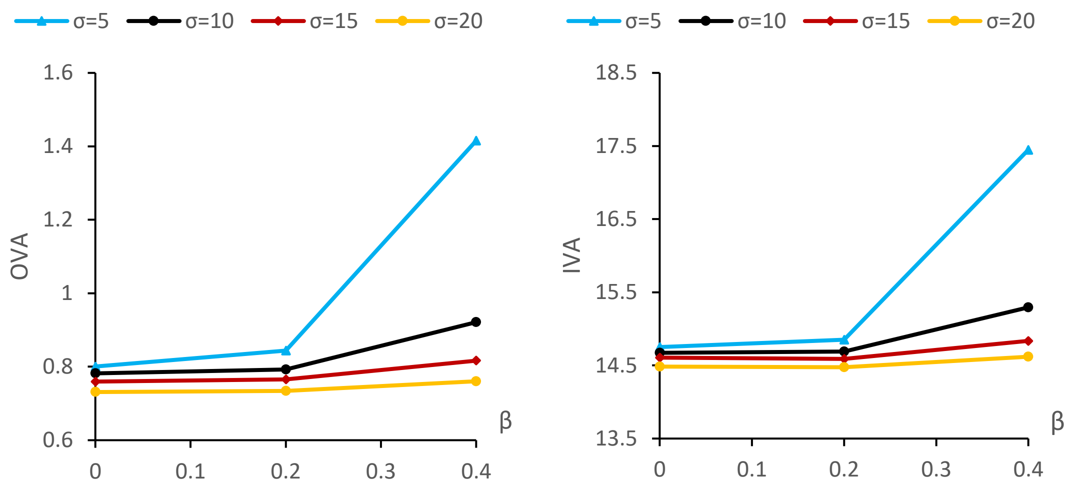

Figure 8b. The effect of β under different σ

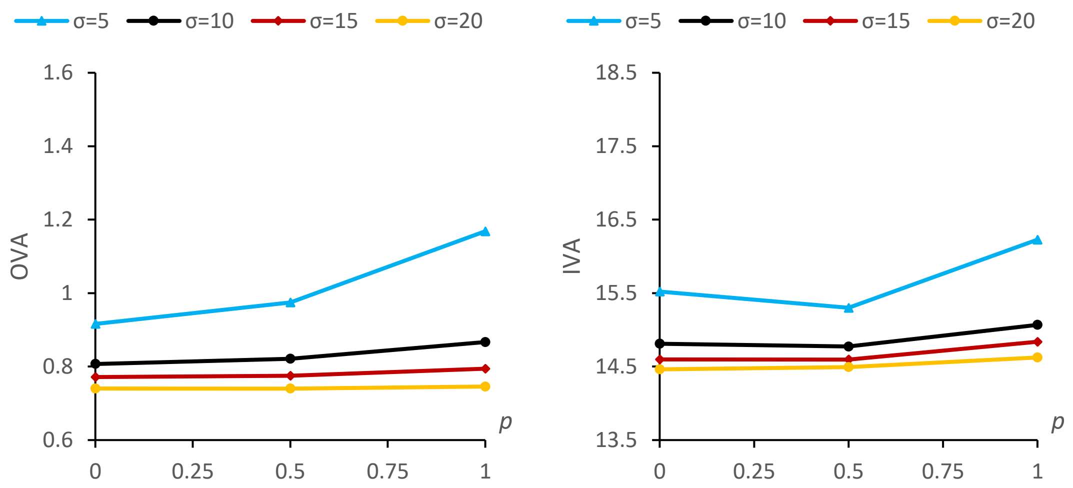

Figure 8c. The effect of p under different σ

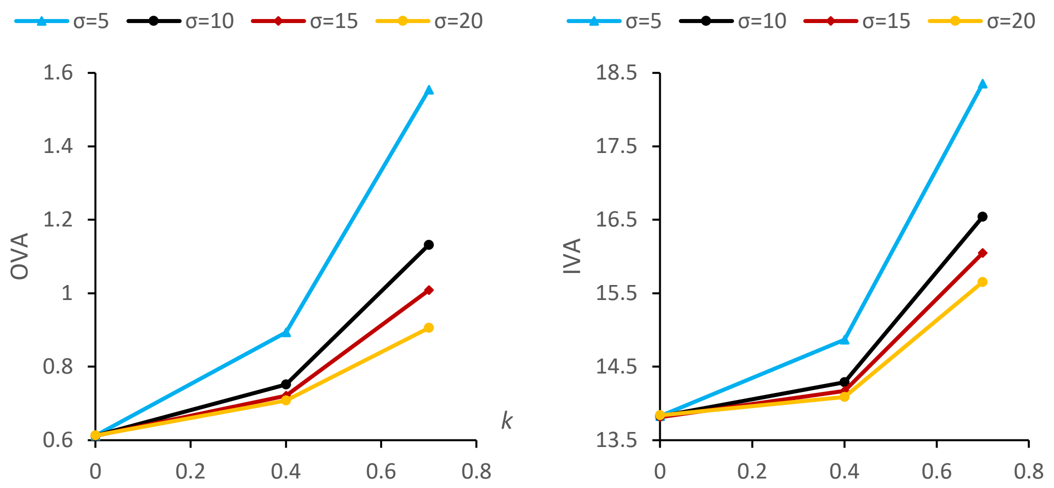

Figure 8d. The effect of k under different σ

Figure 8 Caption: Sensitivity analysis of σ

Figure 8 Alt Text: 4 graphs examining the relationships between CI, β, p, k and order variance amplification ratio as well as between CI, β, p, k and inventory variance amplification ratio under different demand standard deviation.

For CI, a very interesting pattern is observed in Figure 8a. First, under a tight constraint (i.e. $CI = 1.1$), the increase of the demand standard deviation (σ) leads to a decrease in OVA and IVA. In other words, the capacity constraint of return collection plays a 'filter' role in improving system dynamics performance. This can be due to a non-linear capacity constraint and partial backlog in the return collection where a part of the returned product is accumulated over the next period for remanufacturing, meaning that a high demand standard deviation can be effectively attenuated because of this accumulation. Also, when the increase of CI goes from 1.1 to 2.1, opposite effects on OVA and IVA are observed under high and low standard deviation situations. However, a further increase of CI leads to a limited effect on system dynamics performance because the return process is no longer significantly constrained by collection capacity.

These findings extend the results of previous studies on the effects of the capacity constraints of return collection on CLSCs dynamic performance. For example, Dominguez et al. (2019) found that when CI is low, an increase of CI can lead to an increase in OVA but a decrease in IVA. Tombido et al. (2021) found that an increase of CI can either increase or decrease OVA across different types of products, but they failed to explain the reason behind this. Therefore, our results provide a new angle of demand deviation to understand the effect CI on CLSC dynamics. Specifically, when demand deviation is low—meaning that demand is stable—managers are encouraged to invest in return collection capacity expansion to obtain good CLSC dynamic performance. This aligns with the original simulation results in Section 4.1. However, when the standard deviation of customer demand is high, managers may consider adopting a regulated capacity policy (Dominguez et al., 2019) and keep capacity at a relatively low level to improve CLSC dynamic performance.

Figure 8b shows the influence of β on OVA and IVA under different σ. The results indicate that the increase of β has only a small effect on increasing OVA and limited effect on IVA when it is low (i.e. β shifts from 0 to 0.2). However, it has a significant influence on increasing OVA and IVA when it becomes higher (i.e. β shifts from 0.2 to 0.4).

The effects of p are visualised in Figure 8c. The increase of p (from 0 to 50%) leads to a small increase in OVA when $\sigma = 10$ and 15, but has a limited effect when $\sigma = 20$. In addition, p has a limited effect on IVA with its change from 0 to 50%, when the demand standard deviation is relatively high. When p changes from 50% to 100%, this results in a more significant increase in OVA and IVA than from 0 to 50% when $\sigma = 10, 15, 20$. This indicates the robustness of the original simulation results under these scenarios. However, when the demand standard deviation is low (i.e. $\sigma = 5$), an increase of p can lead to an increase of OVA (6.4%) but a decrease in IVA (1.4%) when p changes from 0 to 50%. When p changes from 50% to 100% under the scenario of $\sigma = 5$, OVA and IVA both increase more significantly, which is similar to the pattern observed with a higher demand standard deviation.

Interestingly, a trade-off between OVA and IVA is identified as the change of p from 0 to 50% under the scenario of $\sigma = 5$. That is, OVA is an increasing function of p, but IVA is a decreasing function of p. Given that OVA reflects the capacity-related cost of production, while IVA reflects the cost of holding and backlogging (Cannella et al. 2021; Shaban and Shalaby 2018), an opposite change of OVA and IVA means that there can be an equilibrium point of p. This point can minimise the total cost of CLSC operations induced by order and inventory variance. Finally, Figure 8d indicates that OVA and IVA increase with an increase of k, meaning that the effects of k are robust to the change of σ. This aligns with Hosoda and Disney (2018) and Ponte et al. (2020a).

4.3.2 Sensitivity analysis of T_r

Following Cannella et al. (2021) and Zhou et al. (2017), we use $T_r = 2, 4, 6,$ and 8 to conduct sensitivity analysis. The sensitivity analysis of T_r, as shown in Figure 8, indicates that the results obtained from the original simulation are robust.

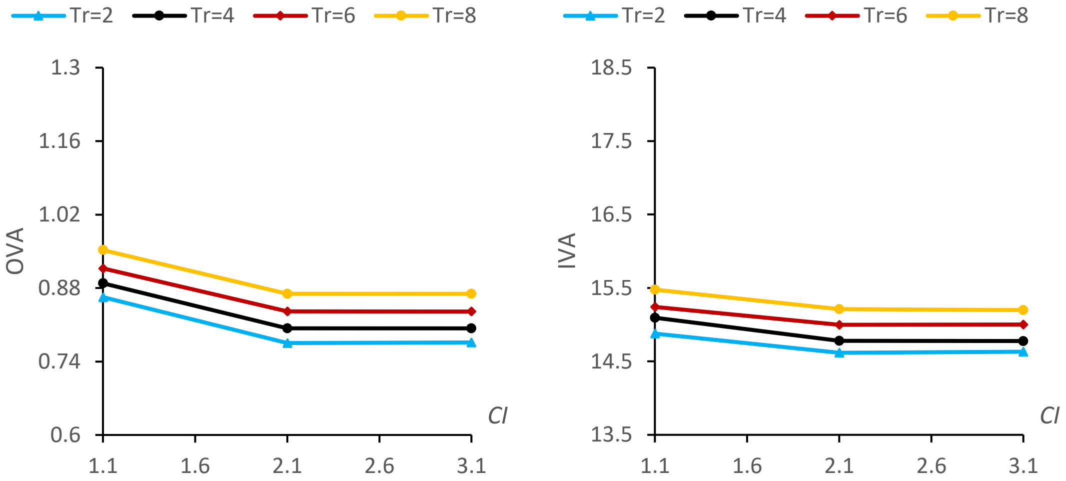

Figure 9a. The effect of CI under different T_r

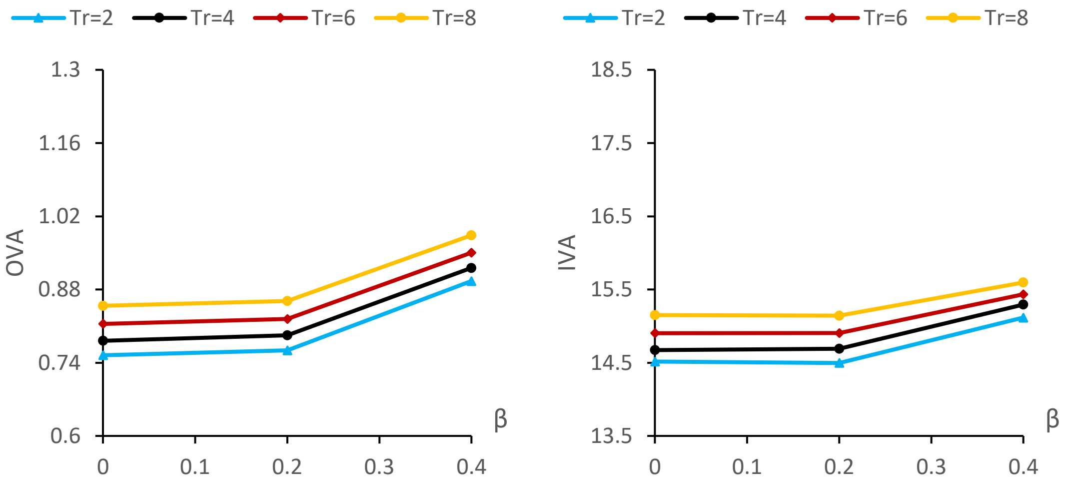

Figure 9b. The effect of β under different T_r

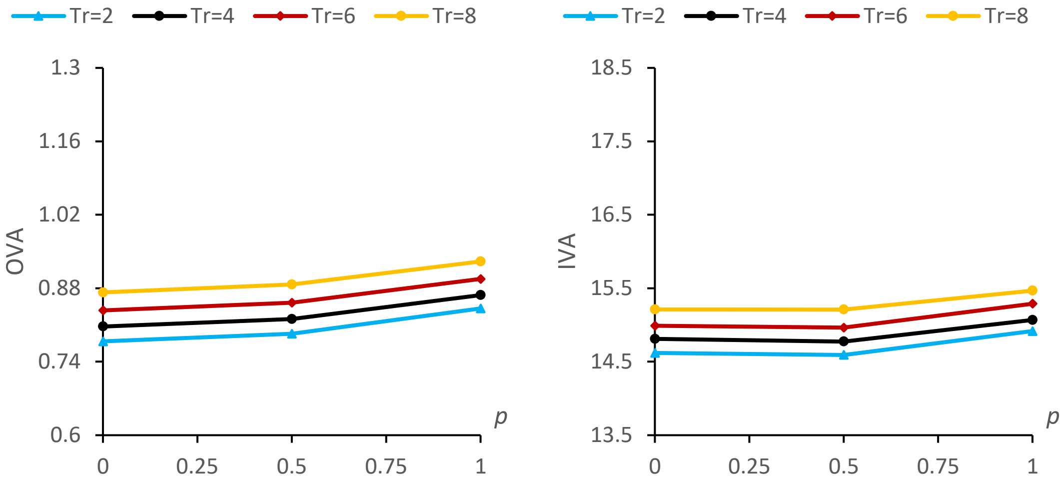

Figure 9c. The effect of p under different T_r

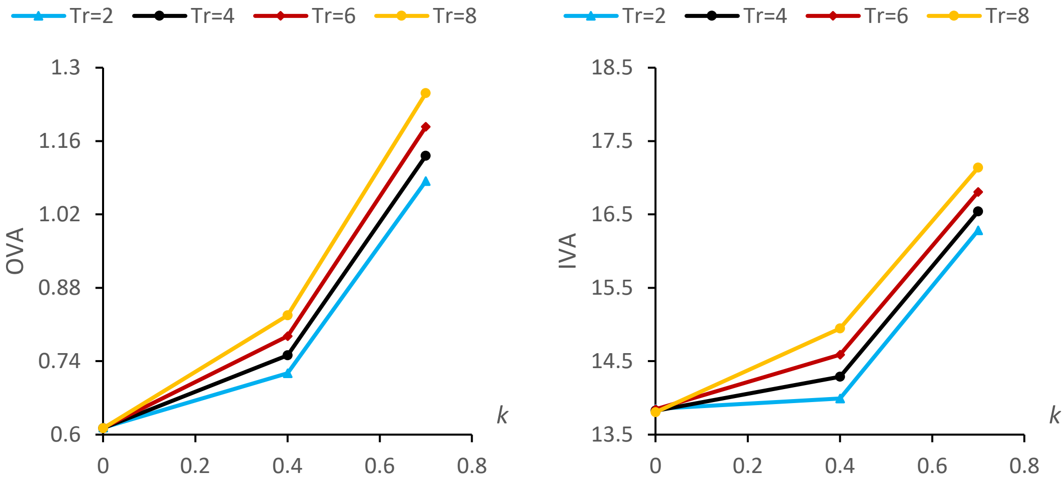

Figure 9d. The effect of k under different T_r

Figure 9 Caption: Sensitivity analysis of T_r

Figure 9 Alt Text: 4 graphs examining the relationships between CI, β, p, k and order variance amplification ratio as well as between CI, β, p, k and inventory variance amplification ratio under different remanufacturing lead time.

First, Figure 9a shows that both OVA and IVA are significantly reduced by an increase of CI when CI is low (i.e. $CI = 1.1$). If CI is sufficiently large, it has limited influence on the value of OVA and IVA under all values of T_r. In addition, Figure 9b shows that an increase of β has a small effect on increasing OVA and limited influence on IVA when β shifts from 0 to 0.2, while β has a stronger influence on increasing OVA and IVA when it changes from 0.2 to 0.4 under different values of T_r. Third, under any value of T_r, p slightly increases OVA but has a very limited effect on IVA when it changes from 0 to 50% (Figure 9c). However, the increase of p 50% to 100% leads to significant increase of OVA and IVA.

4.3.3 Sensitivity analysis of T_i and T_{wip}

Following Ponte et al. (2020), we use $T_i = T_{wip} = 4, 8, 12$ *and* 16 to conduct the sensitivity analysis. The sensitivity analysis of T_i and T_{wip} shows that the original simulation results are robust to different values of T_i and T_{wip}, except for the influence of the return rate (i.e. k) on IVA.

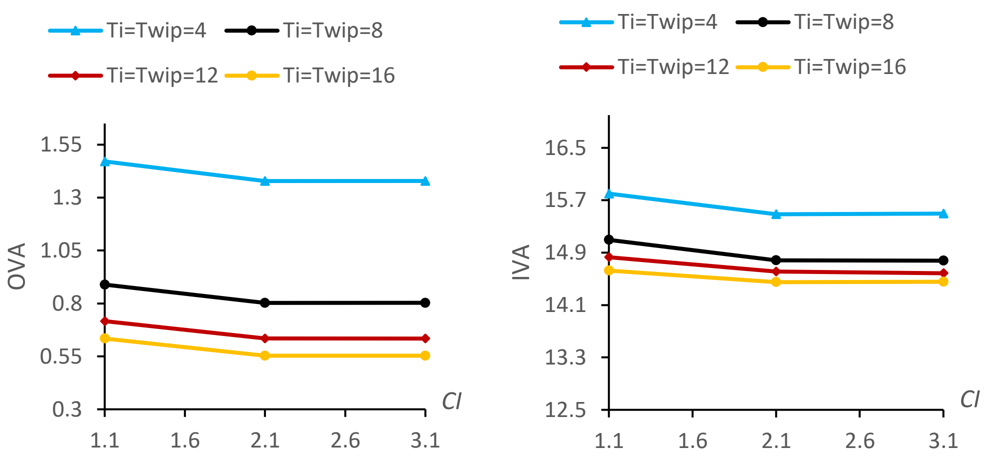

Figure 10a. The effect of CI under different T_i and T_{wip}

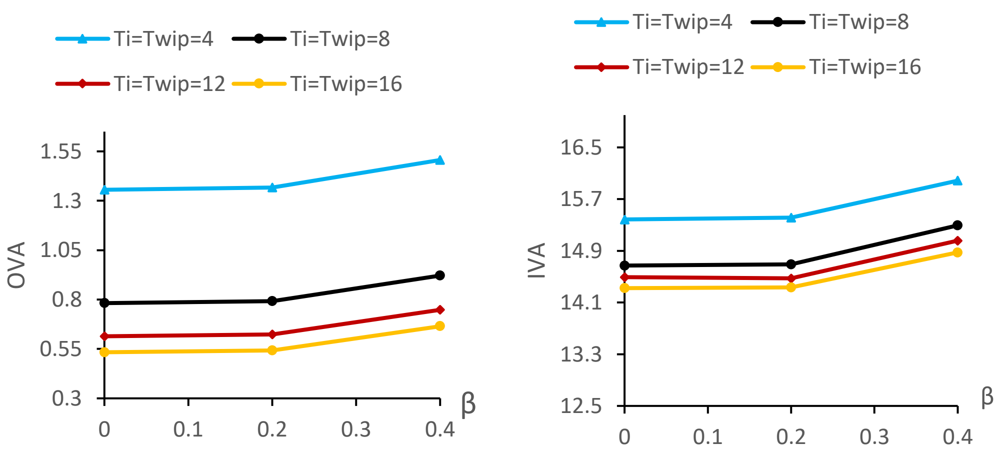

Figure 10b. The effect of β under different T_i and T_{wip}

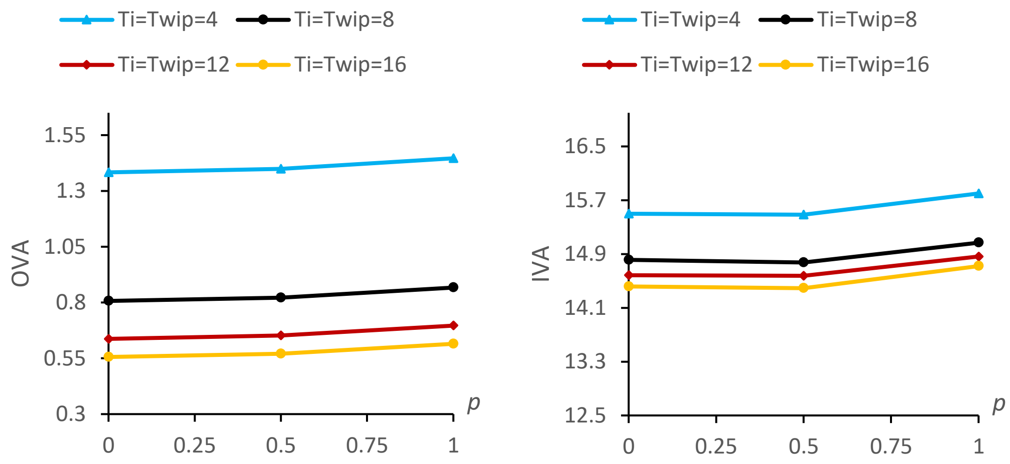

Figure 10c. The effect of p under different T_i and T_{wip}

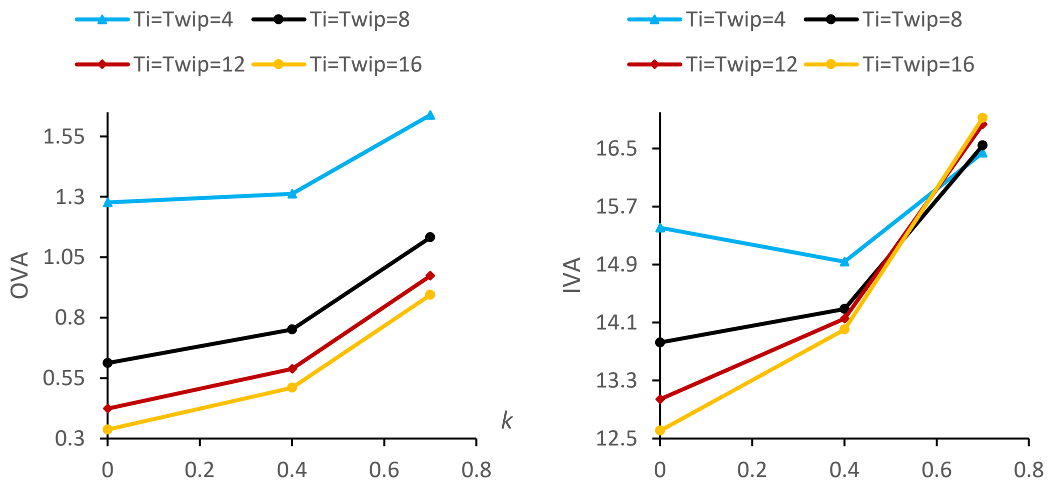

Figure 10d. The effect of k under different T_i and T_{wip}

Figure 10 Caption: Sensitivity analysis of T_i and T_{wip}

Figure 10 Alt Text: 4 graphs examining the relationships between CI, β, p, k and order variance amplification ratio as well as between CI, β, p, k and inventory variance amplification ratio under different proportional controllers.

Specifically, Figure 10a reveals that for all values of T_i and T_{wip}, increasing CI can lead to a significant reduction of OVA and IVA only when CI is low (i.e. $CI = 1.1$). Figure 10b shows that, for the low value of β (between 0 and 0.2), an increase in β has limited impact on OVA and IVA. However, β has a significant influence on increasing OVA and IVA when it becomes higher (i.e. from $\beta = 0.2$ to $\beta = 0.4$). In addition, in Figure 10c, the influence of p on both OVA and IVA remains robust to T_i and T_{wip}, since the increase of p from 0 to 50% leads to a small increase in OVA but has a very limited influence on IVA. A more significant increase of OVA and IVA can be observed when p shifts from 50% to 100%. Finally, Figure 10d shows the effects on OVA of k is robust to the values of T_i and T_{wip}, but the effects of k on IVA are sensitive to a change of T_i and T_{wip}. Specifically, for $T_i = T_{wip} = 8,12,16$, IVA remains an increasing function of k. However, when the values of T_i and T_{wip} are small (i.e. $T_i = T_{wip} = 4$), k has a non-linear effect on IVA. i.e. the IVA is a decreasing function of k for k=0 and 0.4, but an increasing function of k from $k = 0.4$ to $k = 0.7$.

4.3.4 Sensitivity analysis of T_m

Following Turrisi et al. (2013), Zhou et al. (2017) and Lin et al. (2021), we adopt $T_m = 4, 8, 12$ and 16 to perform the sensitivity analysis. The results of the sensitivity analysis of T_m show similar patterns to the results of the sensitivity analysis of T_i and T_{wip}. In other words, the original simulation findings on the effects of CI, β and p on the OVA and IVA are qualitatively held and robust under different values of T_m, while the effects of k on OVA and IVA can be sensitive to a change of T_m under certain situations.

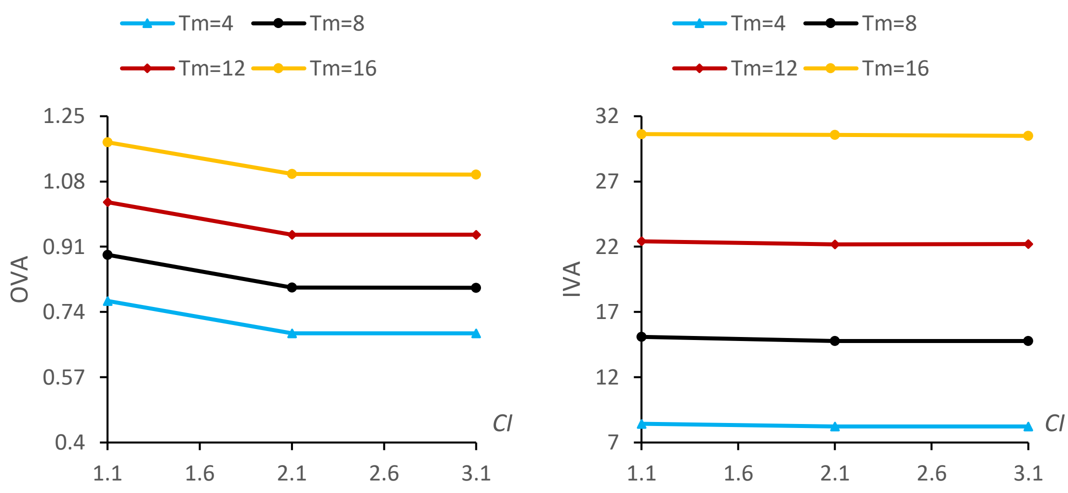

Figure 11a. The effect of CI under different T_m

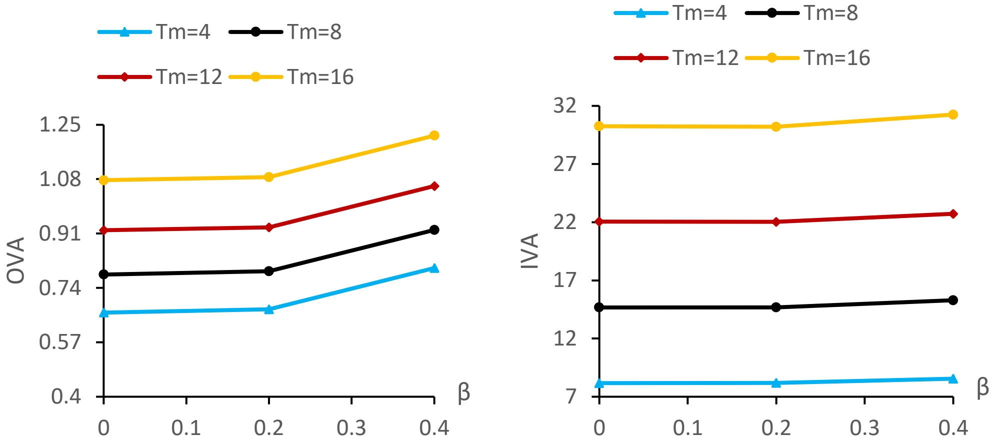

Figure 11b. The effect of β under different T_m

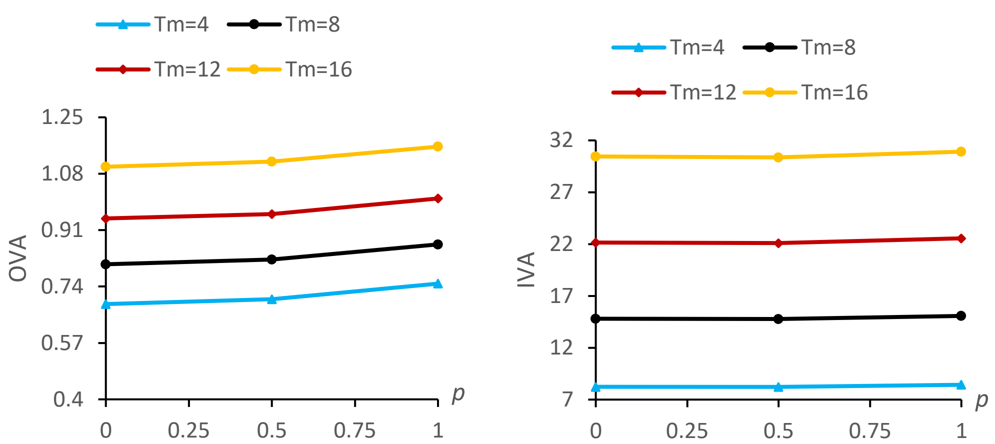

Figure 11c. The effect of p under different T_m

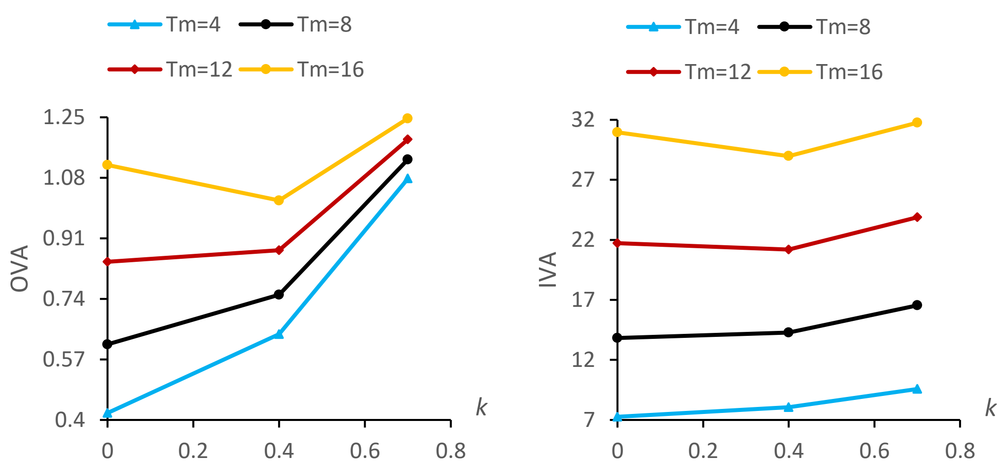

Figure 11d. The effect of k under different T_m

Figure 11 Caption: Sensitivity analysis of T_m

Figure 11 Alt Text: 4 graphs examining the relationships between CI, β, p, k and order variance amplification ratio as well as between CI, β, p, k and inventory variance amplification ratio under different manufacturing lead time.

Specifically, under different values of T_m, Figure 11a shows that an increase of CI can always reduce OVA and IVA when CI is low (i.e. $CI = 1.1$). In Figure 11b, the increase of β can lead to more significant increases in OVA and IVA when it is moderately high (i.e. $\beta = 0.2$), no matter how long T_m is. In Figure 11c, the influence of p on both measures under different values of T_m presents very similar patterns with the original simulation. These results mean that the effects from three independent factors—CI, β and p—on OVA and IVA are robust to a change of T_m. Interestingly, the influence of k on OVA and IVA looks sensitive to the values of T_m. Figure 11d shows that when T_m is not very long, an increase of k can always lead to an increase in OVA and IVA. Specifically, OVA is an increasing function of k when $T_m = 4, 8$ and 12, while IVA is when $T_m = 4$ and 8. With an increase of T_m, the influence of k on OVA and IVA presents a non-linear trend, in which an increase of k can cause a reduction of OVA and IVA when k is small, but can lead to an increase of both measures when k becomes larger. As seen in the previous literature, the non-linear effect of k may explain why the simulation results in Section 4.1 differ from those of Tang and Naim (2004) and Zhou and Disney (2006) which find that an increase of k reduces OVA and IVA. This is because our original model adopts different system structures and parameters (e.g. T_m), even though the negative effects of k on OVA and IVA are also observed in the sensitivity analysis.

5. Discussion

In general, our results show that the complexity of capacitated return collection affects the system dynamics performance of CLSCs in several ways. In particular, our main effects analysis has led to the following findings:

- According to Figure 4a, increasing CI leads to a lower OVA and IVA, and this pattern is especially significant when its value is low. This means that increasing the mean level of SCCC tends to reduce the bullwhip effect, particularly when SCCC is tight.

- Figure 4b demonstrates that once β is relatively high, increasing the value of β can result in stronger OVA and IVA. This suggests that as SCCC becomes more volatile, the bullwhip effect tends to increase. In this sense, highly fluctuated SCCC not only results in difficulties in a production schedule, but also increases the operational costs of CLSCs. Nonetheless, as indicated in Figure 4b, we note that the performance of these systems is moderately robust to low variations of SCCC.
- Based on Figure 4c, if p is relatively high, increasing p can lead to an increase in both OVA and IVA. The results indicate that when customers cannot return used products because of capacity limitations, if they become more willing to wait for the next opportunity to return them (i.e. the increase of the percentage of PBRC), the bullwhip effect tends to grow.
- Figure 4d reports that OVA and IVA are both increasing functions of k. This means that when the volume of customer returns grows, the bullwhip effect of CLSCs tends to increase and higher levels of inventory are required to meet customer demand, impairing the economic performance of these systems.

We note that the last finding aligns with some prior research, such as Hosoda et al. (2018) and Ponte et al. (2019). We also note that we have used 'tend to' in the previous relationships, as the impact of every single factor on each performance metric is considerably moderated by the other factors. This is observable in the interaction analysis, which offers further insights into the dynamics of CLSCs. Interestingly, we observed, from the interaction effect plots between β and k in Figure 6, that the key trade-off mentioned before is particularly relevant when SCCC is highly volatile because this exacerbates the negative effects of increasing the return rate. In addition, our results of the interaction effects of β and CI in Figure 6 reveal that the influence of the volatility of SCCC on the dynamics of CLSCs is only strong when SCCC is tightly constrained. Indeed, it is interesting to highlight that the above interaction plots between β and CI also show when the volatility is very small, reducing the (mean) capacity of SCCC may enhance the dynamics of CLSCs. That is, the effect of SCCC's mean capacity is different depending on the level of volatility.

In addition, the interaction analysis in Figure 5 also reveals that the effect of the volatility of SCCC in the collection system is more significant when the percentage of PBRC is large. In this sense, volatility has a more significant effect on performance metrics (i.e. OVA and IVA) when all customers are willing to wait until they can return used products. Finally, for the interaction effects between p and k in Figure 7, a high percentage of PBRC amplifies the negative effect of the return rate on CLSC performance. Similarly, the interaction effects between p and CI in Figure 7 depicts a high percentage of PBRC amplifies the negative effects of reducing the capacity level of SCCC. In this sense, and considering that an increased percentage of PBRC (i) reduces the performance of CLSCs, and (ii) leads to a higher level of circularity and thus contributes to the reduction of raw material use and waste, a second trade-off emerges between the sustainability and economics of CLSCs.

The sensitivity analysis showed that our results are robust to changes in the system parameters. Also, some new findings have also been identified. First, as the orange lines in both graphs of Figure 8a show, if the variability of demand is high, the increase of the mean capacity level of SCCC can lead to a reduction in CLSC performance (i.e. higher OVA and IVA). This influence of capacity is the opposite of that for stable demand, which is indicated by the blue and black lines in the two graphs of Figure 8a. Second, we observed that, while both metrics (i.e. OVA and IVA) are often minimised when the return rate is 0, there is a chance that they can be minimised for intermediate values of the return rate when manufacturing lead times are very long (i.e. the oranges lines in two graphs of Figure 11d). Third, we found that varying some factors has opposite effects on both performance metrics, such as with the increasing return rate from 0 to 0.4 when the proportional controllers are low (i.e. the blue lines in two graphs in Figure 10d). Given that OVA is representative of capacity-related production costs and IVA is indicative of inventory-related costs (Cannella et al., 2021), there should be equilibrium points that minimise the total costs induced by order and inventory variances.

From our main findings, we derive three key managerial implications:

- *Companies can enhance the operational performance of their CLSCs by simultaneously reducing the mean and volatility of the capacity of a return collection system*. This means that managers should first invest in stabilising their collection capacity. For example, they can build flexible delivery and warehousing practices to hedge disruption risks. Alternatively, they may consider outsourcing the collection process to a third party with a stable capacity, if their own capacity is highly volatile. In this sense, if an organisation can significantly reduce the risks of a collection system, it may be reasonable to establish a tight collection capacity (as long as it can cope with the mean return rate). This may be done by reducing the opening hours of collection stations. However, for exceptional scenario such as unavoidable disruptions risks, it may be reasonable to increase collection capacity by, for instance, increasing the number of collection centres, because this ‘safety capacity’ protects the CLSC against uncertainty and improves its operational performance.

- *Establishing the right capacity for a collection system requires a solid understanding of not only the willingness of customers to return the product, but also the nature of customer demand.* Specifically, the variability of customer demand plays a key role in determining the appropriate capacity level of a collection system. If demand is relatively stable, companies should establish a higher collection capacity to both reduce the bullwhip effect and improve customer satisfaction. In contrast, companies would benefit from using a lower collection capacity when demand variability is high. In this way, analysing the trend and seasonality of demand time series is key to improving the effect of a collection system on the economic performance of CLSCs.
- *Constraints on the collection process uncover new trade-offs between the environmental sustainability and economic performance of CLSCs.* Previous studies (e.g. Hosoda and Disney, 2018; Ponte et al., 2019) have already shown that an increase in the return rate often provokes a decrease in the operational performance of CLSCs, the first key trade-off discussed earlier. In addition, our results reveal that the dynamics of CLSCs can be worse when the percentage of PBRC increases, i.e. more customers are willing to wait when they cannot return the used products. This responsible customer behaviour reduces the environmental effects of economic activities, but makes CLSCs more difficult to manage. Policymakers need to identify these trade-offs carefully because they slow down the transition towards a circular economy. Given that increasing the circularity of CLSCs becomes costly to many organisations, appropriate incentives should be established.

The model we have developed is highly motivated by CLSC operations under the COVID-19 pandemic, given that restrictions and lockdown policies led to continuous fluctuations in the return collection capacities of CLSCs (Staub, 2021). However, the results and implications are also applicable to other capacity constraint scenarios. For example, the result can be applied to other constraint scenarios where capacity can be temporarily lost because of natural disasters (Jabbarzadeh et al., 2018), transportation disruptions (Wilson, 2007) or strikes. Capacity can be boosted as a result of an effective schedule of activities related to return collection, an appropriate arrangement of workforces in collection stations, as well as efficient transportation. This means that, as long as the CLSC faces an SCCC, managers can benefit from our results related to the effect of the collection system when they make decisions about return collection capacity investment, capacity stabilisation or customer return policy implementation.

6. Conclusion

The collection of used products is an integral part of CLSCs. In practice, it is a complex process that is significantly affected by the location and size of collection centres. However, collection has frequently been oversimplified in the academic literature, and its effect on the dynamic behaviour of CLSCs is not yet well understood. From this perspective, this paper has addressed the following research question: *How do* stochastic capacity constraint of a collection station (*SCCC) and its associated PBRC influence CLSC bullwhip effect?* Our study contributes to the supply chain dynamics literature by providing novel findings that enable a deep understanding of the implications of collection.

Through modelling and simulation, together with the design of our experiments, we have seen that the SCCC has an enormous effect on the efficiency and profitability of CLSCs. Specifically, the operational performance of these systems is considerably influenced by: (1) the percentage of products that are collected after their use; (2) the overall mean capacity of SCCC; (3) the volatility of SCCC; and (4) the attitude of customers when they cannot return used products because of capacity limitations. Moreover, the effect of the different factors is not simple. Instead, we have perceived complex interplays between them.

In this sense, a looser SCCC tends to reduce the bullwhip effect and improve customer service in relation to CLSCs. However, the volatility of SCCC significantly moderates this relationship. Indeed, reducing collection capacity may yield operational benefits for CLSCs when return collection processes function in highly stable environments. Also, the effect of the collection capacity depends on the attitude of customers under the PBRC phenomenon. In particular, the effect of SCCC is small when most customers dispose of goods that cannot be returned, and this effect increases as customers become more willing to wait for the next opportunity to return them. As the result, a high percentage of PBRC may induce a higher bullwhip effect and the overall level of operational cost in the CLSC.

Based on the result, this study can guide managers’ efforts to craft effective capacity management strategies for these systems. First, they should develop initiatives to stabilise collection capacity because its volatility greatly diminishes CLSC efficiency. However, this volatility cannot always be notably reduced, particularly in those CLSCs that are more vulnerable to disruptions. Therefore, managers should analyse the disruption risks of their CLSCs, which will help them understand whether they should tailor policies for expanding or limiting the capacity of their collection centres. This study has also identified important trade-offs between sustainability and CLSC performance. This finding may encourage managers to establish a target return rate, given that a high volume of returns may deteriorate the dynamics of CLSCs because of uncertainty in the reverse flow of materials.

Taking this into consideration, this study also has important implications for policymakers. Because high volumes of returns and tight capacity constraints in the collection of used products may greatly reduce the operational performance of CLSCs, decision-making bodies must establish the right incentives for organisations to increase their circularity levels. This would speed up the much-desired transition towards a circular economy. One way to establish such incentives is based on providing stronger financial support for companies that are involved in reverse logistics activities. For instance, tax advantages would help them hedge the potential negative effects of the reverse flow of materials. Nonetheless, it is also essential to facilitate the implementation of efficient and resilient CLSCs, which places a premium on research. In this sense, policymakers should also allow for research of sufficient scale and depth as a key accelerator of the circular economy.

There are several limitations and corresponding future research directions. First, our results have been obtained by analysing a CLSC based on a supplier of new goods and a remanufacturer of used products. It would be interesting to study the implications of collection in longer and wider supply chain structures (e.g. Dominguez et al., 2021). Second, we have assumed that the return rate and consumption lead time are fixed. While these assumptions may hold in certain industrial settings, the impact of stochastic return rates and lead times on bullwhip and customer service can be further explored. Furthermore, future studies may explore in more detail (e.g. optimization) about the implications of collection on the well-known equilibrium between OVA and IVA in CLSCs. Finally, advance analytical approaches such as non-linear control theory can be applied to gain better understanding of the variable relationship based on our model.

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Disclosure Statement

No potential conflict of interest was reported by the author(s).

Data Availability Statement

Data related with this paper is available with authors and will be available upon reasonable request.

Reference

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