On returns and network configuration in supply chain dynamics

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Published in:
Transportation Research Part E, 73, pp. 152-167. 2015.
doi: 10.1016/j.tre.2014.11.008

Abstract

This research focuses on how two common modelling assumptions in the Bullwhip Effect (BWE) literature (i.e. assuming the return of the excess of goods and assuming a serial network) may distort the results obtained. We perform a robust design of experiments where the return condition (return vs. no return) and the configuration of the Supply Chain Network (SCN) (serial vs. divergent) are systematically analyzed. We find an important interaction between these assumptions: the impact of returns on the BWE strongly depends on the SCN configuration. This study highlights the importance of accurately modelling SCNs to properly assess SCNs managers.
Keywords: Returns, Bullwhip Effect, Transport, Divergent Supply Chain, Serial Supply Chain, Simulation.

1. Introduction

Bullwhip Effect (BWE) is undoubtedly one of the most widely investigated phenomena in the modern day Supply Chain Network (SCN) management research (Haughton 2009, Nepal et al. 2012, Cantor and Katok 2012, Li and Liu 2013, Zotteri 2013, Turrisi et al. 2013). In the last decade, several studies have been aimed towards a better understanding of the causes of BWE, as well as their economic consequences and remedies. In order to analyze this phenomenon under real business world conditions, increasingly complex mathematical representations of SCNs (such as multi-product scenarios (Potter et al. 2009, Wangphanich et al. 2010), stochastic lead times (Chatfield et al. 2004, Dominguez et al. 2014), production/distribution capacity constraints (Spiegler and Naim 2014, Cannella et al. 2014a), reverse logistics (Zhou et al. 2005, Turrisi et al. 2013) and so on) have been developed. Despite this, until now, only a few studies have focused on how the modelling assumptions can alter (i.e. overestimating or underestimating) the outcome of the BWE analysis. In this line, the recent work by Chatfield and Pritchard (2013) represents an interesting effort in a relatively new stream on BWE research aimed at improving our understanding of SCN modelling assumptions. These authors analyze the impact of the allowance/disallowance of the return of goods on the BWE in a four echelon serial SCN. Within the former assumption, orders may be negative in size, which essentially model the return of goods. All returns are sent to the upstream partner (i.e. back to the node they originally came from) where they become part of the upstream node's inventory. In the latter assumption orders are truncated at zero units, not allowing the return of goods to the upstream partners.

As underlined by Chatfield and Pritchard (2013), the literature on BWE has almost universally accepted the assumption that orders may be negative in size even though this is an unusual assumption in the literature at large. They prove that SCNs allowing returns may result in a significantly larger BWE. Furthermore, the increase in order variance due to the returns may be quite dramatic at the upper echelons of a SCN. Thus, according to the results of Chatfield and Pritchard (2013), the BWE is overestimated if a real-life SCN that restrict returns is modelled under the negative orders assumption. Overall, their investigation of the impact of returns on the BWE has questioned the default assumption (practically universal in BWE modelling), that returns are permitted.

One extremely interesting research proposal is to analyze whether this ground-breaking finding continues to hold for more complex and realistic SCN configurations than a simple serial SCN. In fact, the configuration of the SCN is assumed to be serially-linked in most of the existent literature related to the BWE (see Wei et al., 2013; Li and Liu, 2013; Trapero et al., 2012; Cantor and Katok, 2012; Liu et al., 2009; O´Donell et al. 2009; Ouyang, 2007; Machuca and Barajas, 2004; Chatfield et al., 2004; Dejonckheere et al., 2004, among others). Thus, we contribute to this line of research by analyzing how these two universally adopted modelling assumptions impact on the BWE and transportation issues, and their modelling and managerial implications. To do so, we compare the performance of the classical serial SCN and that of a complex divergent SCN under the assumptions of allowance/disallowance of negative orders. We first model a four-echelon serial SCN using SCOPE, a Multi-Agent Systems (MAS) based SCN simulation tool (Dominguez et al., 2013). Then, we perform a similar computational experience with a four-echelon divergent SCN model (i.e. 8 Retailer, 4 Wholesaler, 2 Distributor and 1 Manufacturer), in which each node is furnished by two downstream nodes. Finally, we analyze the results obtained by performing an analysis of variance (ANOVA). The results show a strong interaction effect between the two modelling assumptions under analysis, as the impact of the returns assumption on the BWE is different on the two configurations. More specifically, the divergent SCN is less affected by the return of goods than the serial SCN, due to the lower return of goods observed. This reduction in returns is caused by the compensation of independent demand streams received by nodes of the divergent SCN (portfolio effect).

In addition, the divergent SCN experiences a lower increase in transportation costs as compared to those in the serial SCN under the returns assumption. In case of allowing the return of goods, the increase in the volume of transportation due to the two-way transport (and its associated costs) is lower in the divergent SCN than in the serial SCN. In case of a restriction in the return of goods, the “lumpy” demands generated (one or more zero-sized orders separating positive orders) and its associated costs derived from the inactive periods of transport facilities are also lower in the divergent SCN than in the serial SCN.

The rest of the paper is organized as follows: Section 2 presents a background on BWE. Section 3 briefly describes the methodological approach and the model verification. Section 4 describes the serial SCN and the divergent SCN models. Section 5 is the measurement system and the design of experiments. Section 6 presents the results and findings. Section 7 is a summary of modelling and managerial implications and finally Section 8 is the conclusion and limitations of the research.

2. Background: BWE and modelling assumption

Managing a SCN is a dynamic decision task shown to be prone to systematic errors, collectively referred to as the BWE (Cantor and Katok, 2012). The BWE refers to the tendency for order variability to increase within a SCN as orders move upstream from customer sales to production (Croson et al., 2014). BWE is observed frequently in industries (Chen and Lee, 2012), and it has been estimated that the economic consequences of this phenomenon can be as much as 30% of factory gate profits (Metters, 1997). Moreover, the recent, sudden, severe and synchronized trade collapse has led to an exasperation of BWE on several manufacturing sectors (Dooley et al., 2010; Cannella et al., 2014b). Considering the transmission mechanism of global SCN, this exasperation has created a detrimental "domino effect" throughout the world economy. Due to the magnitude of this phenomenon, it has received a lot of attention by SCN managers and researchers (Zotteri, 2013; Li and Liu, 2013).

Jay Forrester (1961) was among the first researchers to describe this phenomenon and called the effect "demand amplification" (Disney and Lambrecht, 2008). Yet, the research into the 'BWE' problem started even prior to Forrester's seminal contribution, and a wide range of seminal works were made prior to its 'rediscovery' in the late 1990's (Holweg and Disney, 2005). In fact, Thomas Warner Mitchell (1924), an economist at the Federal Trade Commission, first identified the mechanisms through which retailers, caught short of supply, increase their orders to suppliers. At the end of the 21st century, Lee, Padmanabhan and Whang (1997a,b) published two of the most popular papers in the field of SCN management. Based on a case study, they identified four causes of Mitchell's *false demand* phenomenon and renamed it "BWE".

Due to the magnitude of the BWE problem, since Mitchell's work (1924) numerous studies have been generated to better understand causes, economics consequences and remedies to this effect. The investigation into this phenomenon has passed through diverse phases (Holweg and Disney, 2005), producing several streams of research (Holweg et al., 2005). Zotteri (2013) identifies three main streams (i.e. theoretical, empirical and natural experiment). The theoretical stream is devoted to the identification of the causes and potential solutions, with a specific focus on information as a potential remedy for the BWE (e.g. Baganha and Cohen 1998; Chen et al., 2000; Cachon and Fisher, 2000; Lee et al., 2004). In the second stream, some contributions use the classic Beer Game (see e.g. Croson and Donohue, 2005; Croson and Donohue, 2006) or one of its variants (Anderson and Morrice, 2000; Cantor and Katok, 2012; Croson et al., 2014) to create empirical data in a controlled environment and test hypothesis on the technical and behavioral causes of the BWE and its potential remedies. Finally, the natural experiment provide evidence for the existence, size and consequences of the BWE in several companies (e.g. Cachon et al., 2007; Dooley et al., 2010; Altamonte et al., 2012; Zavacka et al., 2012; Bray and Mendelson, 2012; Shan et al. 2014).

Similarly, Trapero et al. (2014) identify two different streams. The former concerns the theoretical analysis, which is based on initial assumptions about the underlying demand process and the stock policy in order to develop different expressions that quantify the BWE. The latter is a more practical approach measure of the BWE with actual data collected from different companies involved in the SCN. An analogous classification is provided by Miragliotta (2006), who considers that the BWE literature can be divided into three streams: BWE measurement and empirical assessment, causes of the BWE and remedies for the BWE. In general, we note how researchers tend to differentiate two typologies of works, namely theoretical and empirical.

In the field of theoretical study further sub classifications can be found. For instance, Nepal et al. (2012) identify three streams: the first stream focuses on determining the impact of forecasting techniques, while the other two streams include an examination of the impact of operations management parameters (such as ordering policy, inventory management policy, and production variation and batching) and SCN dynamics (like information sharing) on the BWE. Other authors classify the theoretical studies in relation of adopted methodological approaches for analysing the demand amplification phenomenon. Riddalls et al. (2000) identify four main methodologies: Continuous Time

Differential Equation models, Discrete Time Difference Equation models, Discrete Event Simulation Systems, and Classical Operational Research methods. Disney and Lambrecht (2008) indentify the Laplace Transform method, Z-Transform method, Fourier transform method, H-infinity control, Ideal Filter, System Dynamics and Discrete Event Simulation. Nilakantan (2010) divide the study of the dynamics of SCN systems in three important dimensions, namely: the setting: Deterministic vs. Stochastic; the focus: Control and Stability vs. Optimization; and the time frame of reference: Continuous Time vs. Discrete Time.

Several further classifications and taxonomies of the different streams of the BWE studies have been produced (e.g. Dejonckheere et al., 2004; Disney et al., 2004; Geary et al., 2006; Lalwani et al., 2006; Sarimveis et al., 2006). However, to the best of our knowledge, there is a stream of the theoretical studies dealing with the BWE that has not yet been explicitly acknowledged by the scientific community: the studies aimed at gaining a higher understanding of SCN modelling assumptions. Despite the importance of this topic, few studies have focused on how the adoption of specific assumptions can affect the results of the BWE assessment. In this stream, one of the pioneer efforts is represented by the study of Towill et al. (2007). They propose a framework for properly studying the BWE, indicating the appropriate typology of endogenous input that can be adopted in BWE analysis in order to study different characteristics of the SCN. Recently, Chatfield (2013) and Chatfield and Pritchard (2013) present two works. The former study show how the assumption that a multi-stage SCN can be faithfully modeled for BWE investigation purposes as a set of two-stage models is faulty, and that the decomposability assumption leads to significant underestimation of the phenomenon. The latter study shows how that the assumption of “negative orders” systematically overestimates the BWE, and it is the starting point of our research.

Our investigation fits within this new stream of research: we provide insights on how the assumption of “negative orders” has a different impact on the BWE depending on whether the SCN shows a serially-linked configuration or a divergent configuration. In other words, we show how a strong interaction between two modelling assumption may distort the results obtained for the BWE.

3. Methodology and model verification

Due to the complexity of SCN management, it is very difficult for managers and decision-makers to predict the effects that new management policies will have on end-customers and/or the global performance of the SCN and, consequently to decide which are the best strategies. Thus, the existence of modeling tools able to cope with the complex characteristics of modern SCNs (such as internal and external uncertainties and the high number of members) is very helpful to managers and of great benefit for enterprises (Dominguez and Framinan, 2013).

Classical operational research and analytic methods are not always able to handle the characteristics of complex SCNs (Long and Zhang, 2014; Lee and Kim, 2008; Holweg and Disney, 2005; Riddals et al., 2000). Therefore other methodologies are required to model these kind of systems. The use of simulation to model SCNs has increased in the past years, due to its ability to handle the dynamics and stochastic behavior of SCNs and to enable managers to analyze and evaluate the effects of alternative processes or operation modifications (Chan and Prakash, 2012; Stefanovic et al., 2009; Munoz and Clements, 2008; Chatfield et al., 2001). Specifically, Multi-Agent Systems (MAS) has been used to model multiple problems involving systems of differing size and structure due to its scalability and flexibility (Jetly et al., 2012).

There is great interest in modeling SCNs as (MAS) (Surana et al., 2005; Pathak et al., 2007) because there is a natural correspondence between SCN participants and agents in a simulation model, since SCNs tend to be decentralized systems with participants acting independently (Long and Zhang, 2014). MAS is a promising alternative to the commonly used mathematical programming optimization techniques due to its ability to implement sophisticated rules of agents on the local level and to relate them to the global outcomes (Mizgier et al., 2012). Furthermore, MAS have the capacity to consider the interactions between large numbers of heterogeneous firms, allowing SCN managers to improve their understanding of the whole system and predicting the consequences of singular interventions on the global performance (Hearnshaw and Wilson, 2013).

The use of MAS applied to SCN modeling in the past years resulted in the development of several MAS frameworks, SCN simulation tools and applications on industry, such as those of Yu and Wong (2015), Long and Zhang (2014), Medini and Rabénasolo (2014), Long (2014), Ogier et al. (2013), Dominguez and Framinan, (2013), Santa-Eulalia et al.

(2012), Mishra et al. (2012), Govindu and Chinnam (2010,2007), Chatfield et al. (2007, 2006), Julka et al. (2002a,b), and Swaminathan et al. (1998) among others.

The SCNs to be analyzed in this paper have been modeled using SCOPE (Dominguez and Framinan, 2013), a MAS-based software platform specifically designed for the simulation of complex SCN structures. The simulator was implemented in Java and uses Swarm (a software platform for MAS development). In order to verify SCOPE, we perform a benchmark with results provided by other major cited authors in the SCN literature, in particular with Chen et al. (2000), Dejonckheere et al. (2004) and Chatfield et al. (2004) (see Table 1). The SCN modelled is a mono-product four-echelon serial formation. Table 1 summarizes the Total Variance Amplification in each echelon i ($TVAmp_i$) provided by the different authors. $TVAmp_i$ measures the total amplification of orders for a given echelon i (see Section 5 for more details). The first row in Table 1A shows the results analytically obtained by Chen et al. (2000) for a given set of values for the parameters of the SCN (lead time, forecast, etc.). The next row shows the results obtained by Chatfield et al. (2004) using SISCO (a MAS-based software for SCN simulation) for an identical set of model parameters. In the third row, the results obtained by SCOPE for the same set of model parameters are shown. Table 1B summarizes the comparison with Dejonckheere et al. (2004) for a different set of model parameters. These authors calculate $TVAmp_i$ using a Control Theory methodology. As in Table 1A, it follows the results provided by Chatfield et al. (2004) using SISCO and the results obtained by SCOPE. For further information on SCOPE and on the validation process please see Dominguez and Framinan (2013) and Dominguez et al. (2014).

	Retailer	**Wholesaler**	**Distributor**	**Factory**
A	$TVAmp_i$			
Chen et al. 2000	1.89	3.57	6.74	12.73
Chatfield et al. 2004 vs Chen et al. 2000	1.90	3.59	6.70	12.84
SCOPE vs Chen et al. 2000	1.90	3.53	6.66	12.58
B	$TVAmp_i$			
Dejonckheere et al. 2004	1.67	2.99	5.72	11.43
Chatfield et al. 2004 vs Dejonckheere et al. 2004	1.67	2.99	5.72	11.43
SCOPE vs Dejonckheere et al. 2004	1.71	3.10	5.96	11.93

Table 1. Model verification.

4. Model details

As mentioned before, we model a serial SCN and a divergent SCN. The serial SCN is identical to that presented in Chatfield et al. (2004) or Chatfield and Pritchard (2013). It has four stages (i=1,..,4), with one factory, one distributor, one wholesaler and one retailer (Figure 1). The lower node places orders to its next upper node and this node fills these orders. The customer does not fill orders and the factory places orders with an outside supplier. A detailed description is provided in Chatfield et al. (2004) and Chatfield and Pritchard (2013).

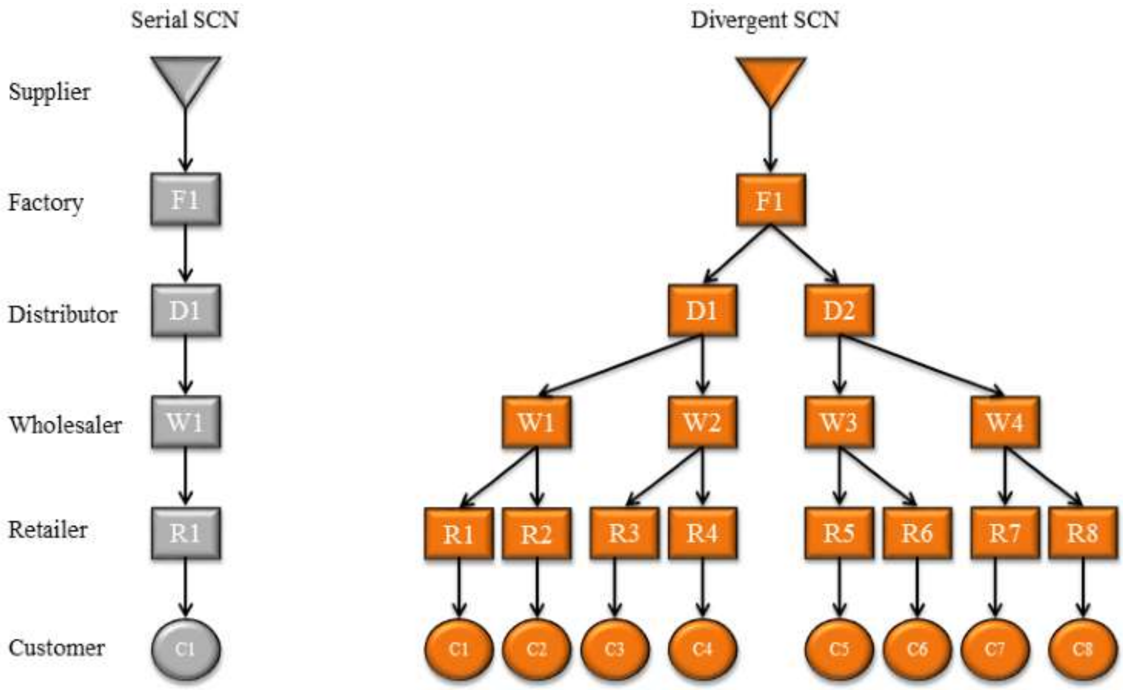

Figure 1. SCNs under analysis.

A divergent SCN is characterized by a tree-like structure, where every stock point in the system receives supply from exactly one higher level stock point, but supplies to one or more lower level stock points (Hwarng et al., 2005). In order to facilitate a comparative analysis the divergent SCN modelled has to be similar to the serial SCN. Hence, the resultant SCN has the identical values of parameters, the same number of stages and, due to the divergent topology, an increasing number of nodes per stage. Due to the prospective nature of this work, the resultant divergent SCN has the minimum complexity, and so, the structure of the SCN maintains the vertical symmetry with each node supplying two nodes downstream (see Figure 1).

We model the divergent SCN by adapting the serial SCN model from Chatfield et al. (2004) and Chatfield and Pritchard (2013), as follows:

- **Customers Demand**. A demand $C{,}j$ is observed by each customer j, following the same normal distribution with mean $\mu_{C,j}$, estimated by $\overline{D}_{C,j}$, and variance $\sigma^2_{C,j}$, estimated by $s^2_{C,j}$.

- **Lead Time**. L_{ij} the lead time of a node *(i,j)* is assumed stationary, independent and identically distributed with mean $\mu_{L_{ij}}$ estimated by $\overline{L}_{ij}$, and variance $\sigma^2_{L_{ij}}$estimated by $s^2_{L_{ij}}$. The lead time of interest, or "protection period", in periodic order-up-to systems, may also include safety lead time or other constant additions to the physical lead time, depending on the inventory policy or other situational characteristics. According to Chatfield and Pritchard (2013), all nodes in the SCN use the (*R*, *S*) policy (where *R* is the review period and S is the order-up-to level) with *R*=1, and the time period of protection of a node *(i,j)* is L_{ij}+*R.*

- **Lead-Time Demand**. Let X^t_{ij} be the demand received by a node *j* in the stage *i* during the protection period L+R. Then X^t_{ij} has mean μ_X that we estimate by $\overline{X}^t_{ij}$, and variance σ^2_X that we estimate by $s^2_{X^t_{ij}}$. Being D^{t+k}_{ij} the demand received by a node *j* in the stage *i* at time $t + k$, we obtain X^t_{ij} for an order placed at time *t* by the convolution:

$$X^t_{ij} = \sum_{k=0}^{L+R} D^{t+k}_{ij} \tag{1}$$

- **Inventory Policy and Forecasting**. The order-up-to level, S^t_{ij}, is the base stock that allows the system to meet the demand during the time period L_{ij}+R:

$$S^t_{ij} = \overline{X}^t_{ij} + z s_{X^t_{ij}} \tag{2}$$

  Thus, at the beginning of every period *t*, each node *j* in the stage *i* will place an order to raise or lower the inventory position to S^t_{ij}. $s_{X^t_{ij}}$ is an estimation of the standard deviation of X^t_{ij}. As in Chatfield et al. (2004), the safety factor is $z = 2.0$ (service level of 97.72%). To update S^t_{ij}, a node *j* in stage *i* can access to the demand data from previous periods (which are used to forecast $\overline{D}^t_{ij}$, the expected average demand at time t, $\bar{D}_{ij}^{t}$, and its variance, $s_{D_{ij}^{t}}^{2}$), and to the lead time data from previous periods (which are used to forecast the expected average lead time at time period t, $\bar{L}_{ij}^{t}$, and its variance, $s_{L_{ij}^{t}}^{2}$), and uses this information to generate forecasts for the average lead-time demand mean $\bar{X}_{ij}^{t}$ and variance $s_{X_{ij}^{t}}^{2}$, as indicated in (3) and (4), respectively:

$$\bar{X}_{ij}^{t} = \left(\bar{L}_{ij}^{t} + R\right)\bar{D}_{ij}^{t} \tag{3}$$

$$s_{X_{ij}^{t}}^{2} = \left(\bar{L}_{ij}^{t} + R\right)s_{D_{ij}^{t}}^{2} + {\bar{D}_{ij}^{t}}^{2} s_{L_{ij}^{t}}^{2} \tag{4}$$

To estimate ($\bar{D}_{ij}^{t}, s_{D_{ij}^{t}}^{2}$), as in Chatfield and Pritchard (2013), each node uses a *p*-period moving averages (*MA*(*p*)) and a *p*-period moving variances (*MV*(*p*)) with *p*=15. To estimate ($\bar{L}_{ij}^{t}$, $s_{L_{ij}^{t}}^{2}$), each node uses running averages, which utilizes data available from all previous periods.

5. Metrics and experiments design

In order to measure BWE we adopt the Total Variance Amplification (Chen et al., 2000; Chatfield et al., 2004), $TVAmp_i$. Furthermore, in order to enhance the comparison analysis between the different SCNs, the Bullwhip Slope metric described in Cannella et al. (2013) is also adopted. Finally, a Zero Replenishment metric (Cannella and Ciancimino, 2010; Sajadi et al., 2011) is used to measure the lumpy demands generated when returns are not allowed. These metrics are described below:

1. Total Variance Amplification ($TVAmp_i$). It measures the total (or cumulative) amplification of orders, and it is defined as the ratio of the variance of orders placed by node at a generic echelon i to the variance of orders placed by the customer (equation 5).

$$TVAmp_i = \frac{s_{O_i}^{2}}{s_{d}^{2}} \tag{5}$$

In the serial SCN the parameter required to compute the $TVAmp_i$ on each stage is taken from the only node in the stage. On the contrary, in the divergent SCN it is necessary to find an aggregate measure for the whole stage (Dominguez et al., 2014). To obtain this measure, the orders of every node *j* in stage *i* (O_{ij}) are considered at the same time and added, resulting in an aggregate order pattern for stage *i*: $AO_i = \sum_{j=1}^{n_i} O_{ij}$, being n_i the number of nodes in stage *i*. Following the same procedure, the aggregate end customer demand pattern can be obtained as $Ad = \sum_{j=1}^{n_C} O_{Cj}$, being n_C the number of customers. Then, the aggregate variance of each stage ($\sigma^2_{AO_i}$, σ^2_{Ad}) can be estimated ($s^2_{AO_i}$, s^2_{Ad}), so $TVAmp_i$ can be written as:

$$TVAmp_i = \frac{s^2_{AO_i}}{s^2_{Ad}} \tag{6}$$

Since all customer demands are assumed to be independent and each node places orders independently, the aggregate variance in stage *i* is the sum of the variances of orders of each node *j* in stage *i* ($\sigma^2_{O_{ij}}$, $\sigma^2_{O_{Cj}}$), estimated by ($s^2_{O_{ij}}$, $s^2_{O_{Cj}}$), and thus, the calculation of $TVAmp_i$ can be written as:

$$TVAmp_i = \frac{\sum_{j=1}^{n_i} s^2_{O_{ij}}}{\sum_{j=1}^{n_C} s^2_{O_{Cj}}} \tag{7}$$

2. The Bullwhip Slope (*BwSl*). It summarizes the ratios obtained for each stage into a single measure (the slope of the linear interpolation), thus allowing a complete comparison between different SCNs at the network level (equation 8). A high value of the slope indicates a fast propagation of the BWE through the SCN, while a low value speaks for a smooth propagation. This metric can give an important and concise overview of the properties of an *n*-echelon SCN both in terms of bullwhip and inventory stability using just one indicator instead of the *n* values required by $TVAmp_i$ (Cannella et al. 2013).

$$BwSl = \frac{K\sum_{i=1}^{K} p_i TVAmp_i - \sum_{i=1}^{K} p_i \sum_{i=1}^{K} TVAmp_i}{K\sum_{i=1}^{K} p_i^2 - \left(\sum_{i=1}^{K} p_i\right)^2} \tag{8}$$

K is the total number of echelons
p_i is the position of the *i*th echelon

3. Zero Replenishment (*ZR*). For a periodic review order policy, a zero replenishment event is defined as the event in which, during a review period, a tier does not place orders (Cannella and Ciancimino, 2010). An order pattern characterized by a significant number of zero-replenishment occurrences is known in the literature as sporadic, intermittent or lumpy. In a given time horizon, if the demand is a positive and stationary signal and the parameters of the inventory replenishment rule remain unaltered, the occurrence of the zero-replenishment phenomenon could be indicative

of an erroneous excessive dimensioning of previous orders (Cannella and Ciancimino, 2010).The zero-replenishment metric (equation 9) is the total amount of the zero-replenishment phenomenon occurrences in the observation period T:

$$ZR_{ij} = \sum_{t=0}^{T} x_{ij}(t)$$
$$x_{ij}(t) = \{1 \; if \; O_{ij}(t) = 0; 0 \; if \; O_{ij}(t) \neq 0\} \tag{9}$$

We design a full factorial set of 12 experiments to analyze the impact of the two modeling assumptions under different lead time variability: 2 (Serial SCN vs. Divergent SCN) x 2 (Returns vs. No Returns) x 3 (Lead Time c.v.=0.0; c.v.=0.25; c.v.=0.50). In order to simplify the comparative analysis between the serial SCN and the divergent SCN, we maintain other modeling parameters fixed in the simulations. We perform 50 replications of 5,200 periods each, with the data from the first 200 periods of each replication removed as warm-up. Table 2 summarizes the design of experiments.

Configuration of the SCN	**Returns assumption**	**Lead time variance**	**Common initial values**
			Review period (*R*) = 1
		c.v. = 0.50	*z* = 2
Serial SCN	Returns allowed		
			p = 15
		c.v. = 0.25	
			Lead time mean= 4
Divergent SCN	Returns not allowed		
		c.v. = 0.00	Demand mean = 50
			Demand c.v. = 0.40

Table 2. Design of experiments.

6. Results

We present the result of the experiments by first performing an analysis of variance (ANOVA) on the simulation data in order to find out the significance of the experimental factors, and then focusing on the different impact that the return of goods has on several aspects of the serial and the divergent SCNs.

The different impact of returns on the BWE in serial and divergent SCNs.

We perform an ANOVA on the three experimental factors (i.e. configuration of the SCN, returns assumption, and lead time variance) using *BwSl* as the response variable. The results show a very good fit with R^2 (see Table 3). All the experimental factors are found to be statistically significant (p<0.001) at the 95% confidence level. The results of this model suggest that the configuration of the SCN has a strong important impact on the BWE in addition to the lead time and the returns assumption, as we will see in the following sections of the paper. More specifically, the BWE is higher for the divergent SCN, as it can be seen from Figure 2.

Source	DF	F	P	R^2(%)
Adjusted Model	11	1980.153	0.000	99.0
SCN_Configuration	1	1595.208	0.000	87.5
Returns_Assumption	1	13172.919	0.000	98.3
Lead_Time	2	2086.126	0.000	94.8
SCN_Configuration * Returns_ Assumption	1	2197.302	0.000	90.6
SCN_Configuration * Lead_Time	2	103.062	0.000	47.5
Returns_ Assumption * Lead_Time	2	48.407	0.000	29.8
SCN_Configuration* Returns_ Assumption * Lead_Time	2	170.533	0.000	59.9
Error	228			
Total	240			

Table 3. Summarized ANOVA results for *BwSl*.

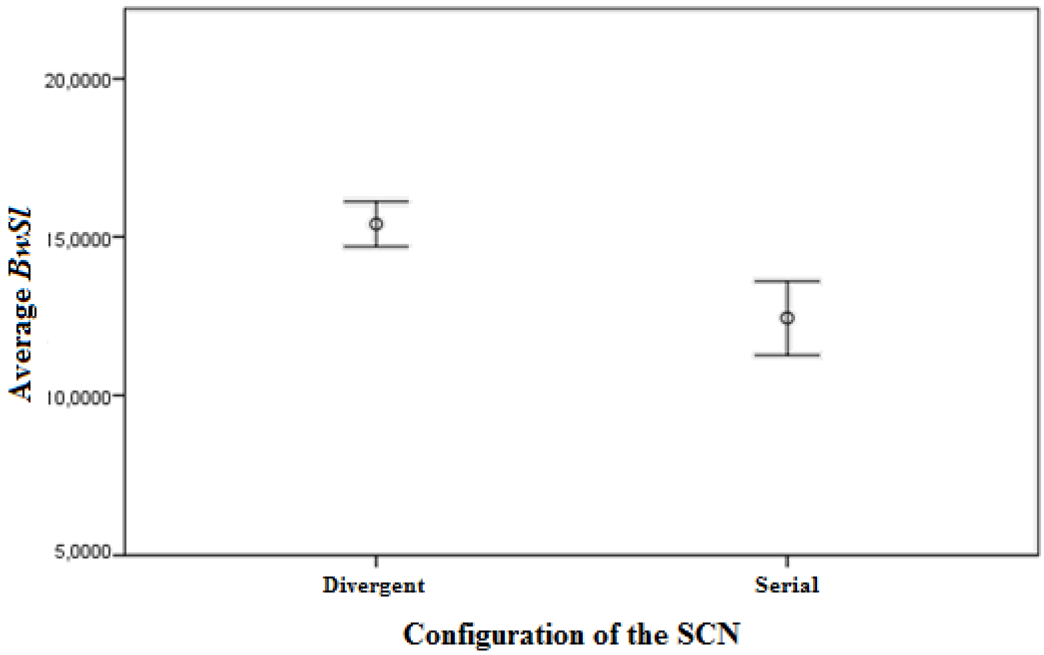

Figure 2. Impact of the configuration of the SCN on the average *BwSl* with 95% confidence level.

The three interactions between the experimental factors are also statistically significant. There is a very strong interaction between the configuration of the SCN and the returns assumption, which is dominant over the others (R^2=90.6%). An interaction plot between the two experimental variables is shown in Figure 3. We can appreciate in this figure the strong interaction between the experimental factors, since the interaction lines are crossed. More specifically, when moving from allowing returns to not-allowing returns, the decrease in the BWE for the divergent SCN is lower than for the serial SCN.

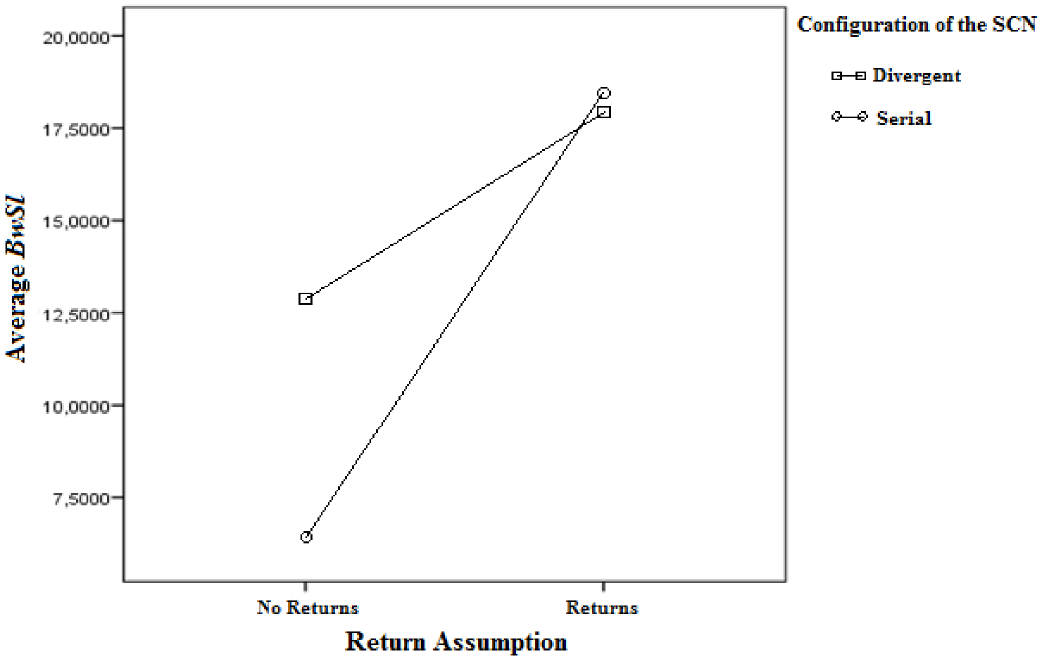

Figure 3. Interaction plot of the Returns Assumption and the Configuration of the SCN.

Figure 4 summarizes the main results obtained from the simulation runs, showing the BWE under the returns allowance/disallowance assumption for the serial SCN (left column) and the divergent SCN (right column) for different lead time variances.

First of all we focus on the serial SCN. Simulation output shows how the assumption of allowing returns has an important impact on the BWE (Chatfield and Pritchard, 2013). By neglecting returns, the variability of orders is reduced and thus the BWE is also reduced for all the experimental design.

Now we focus on the differences between the serial and the divergent SCNs. We note significant differences between both SCNs under the studied assumption: the high increase in BWE observed for the serial SCN by allowing returns (Figure 4, left column) is not observed for the divergent SCN (Figure 4, right column), where this increase is much lower (see also Figure 3). In fact, the interaction between these two factors (i.e. returns assumption and SCN configuration) has been found to be the most important one, with R^2=90.6%.

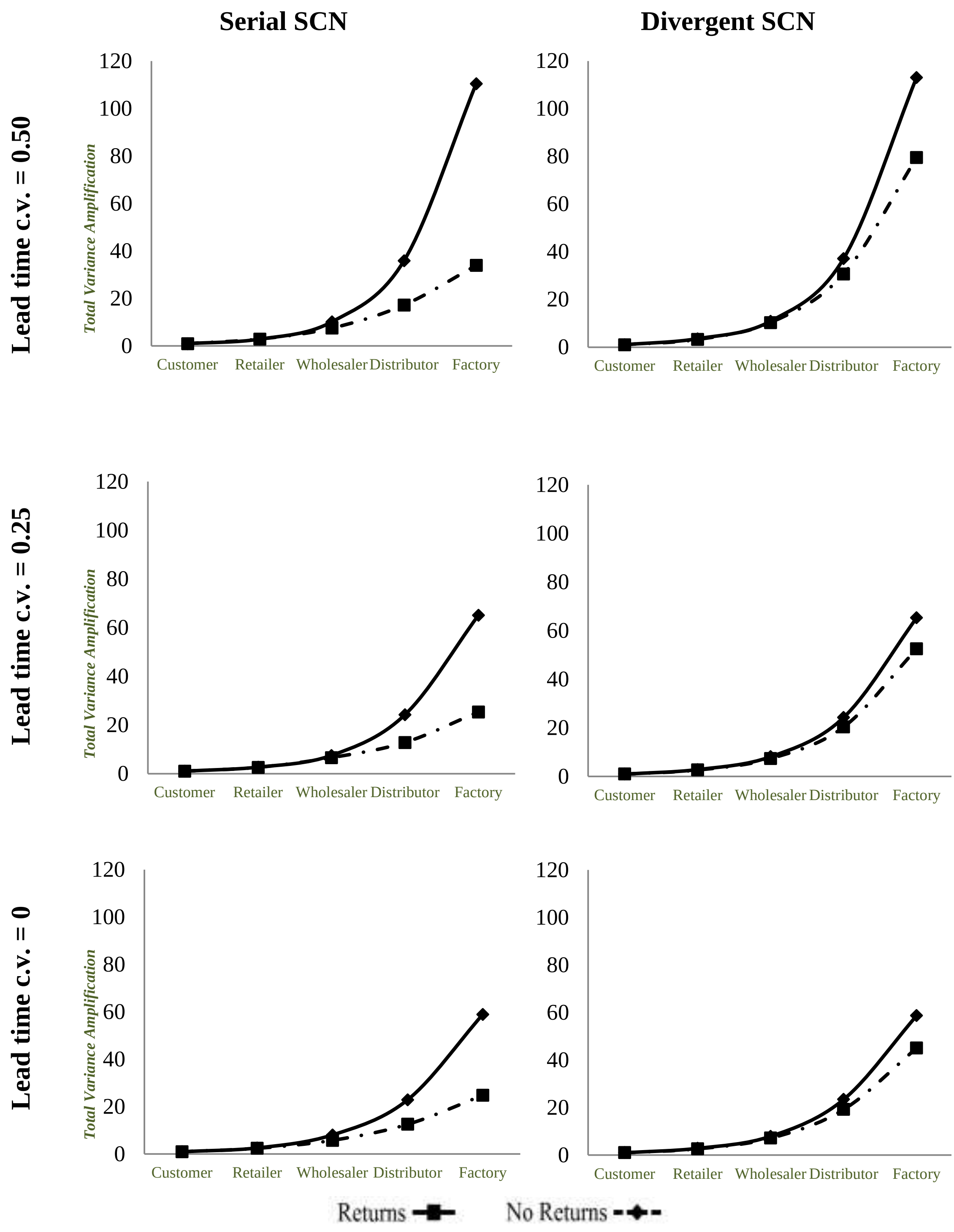

Figure 4. The different impact of the returns assumption on serial and divergent SCNs.

In order to quantify and to compare the impact of returns on the global performance of both SCNs we use the *BwSl* metric. Figure 5 shows the percentual increase of the bullwhip slope ($\Delta BwSl$) derived from the returns allowance assumption. As we can note from this figure, the impact of returns has actually a substantial higher impact on the serial SCN as compared to that of the divergent SCN: maximum increase for the serial SCN is above 200% while the maximum increase for the divergent SCN is below 50%.

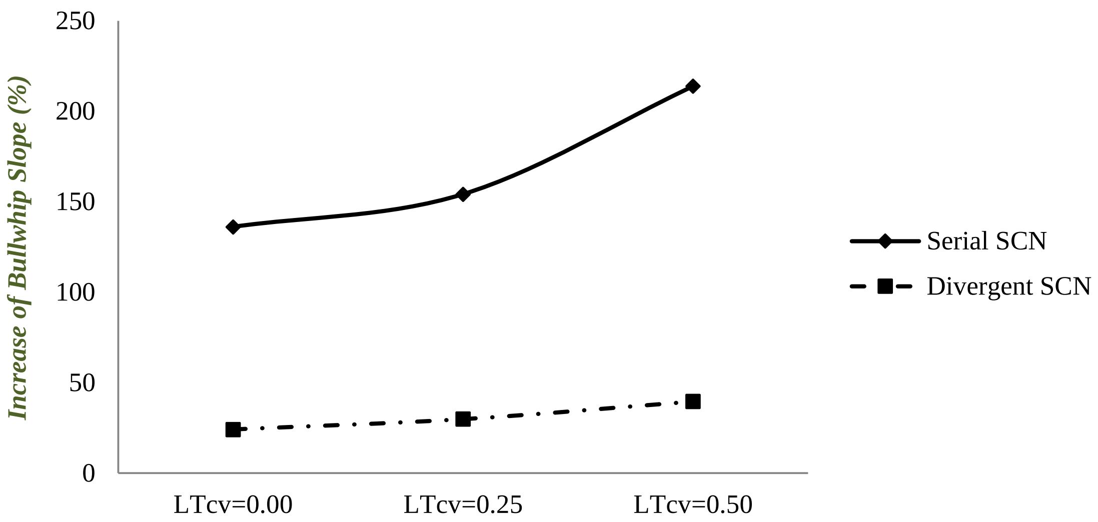

Figure 5. Differences in BWE derived from the returns allowance assumption.

In view of this analysis we can formalise the first three findings of our work as follows:

- *Both modelling assumptions (i.e. returns allowance/disallowance and SCN configuration) are found to have a significant impact on the BWE.*
- *The magnitude of the impact of returns on BWE strongly depends on the SCN structure.*
- *Under identical parameters and market conditions, the allowance of returns has a higher impact on a serial SCN than on a divergent SCN.*

The different impact of lead time variability on returns and BWE in serial and divergent SCNs

Here we address the different importance of lead time variability on the returns assumption depending on the SCN configuration. First, we focus on the impact that the lead time variability has on the returns assumption for both SCNs.

In Figure 5 we note how the observed differences in performance between the serial and the divergent SCNs caused by the returns assumption are affected by the lead time variability in different magnitudes: the serial SCN shows an exponential increase of $\Delta BwSl$ as the lead time variability increases while the divergent SCN shows a linear increase of $\Delta BwSl$. In addition, the slope of the linear interpolations of both curves (38.86 for the serial SCN and 7.75 for the divergent SCN) confirms that the returns allowance assumption is more sensitive to the lead time variability in case of a serial SCN than in case of a divergent SCN. This significant interaction between the three experimental factors (i.e. the lead time, the SCN configuration and the returns assumption) is also highlighted by ANOVA, with R^2=59.9%.

Now we focus on the scenario of returns disallowance, and we analyze the impact of the lead time variability on both SCNs. If we plot the differences in BWE between the serial SCN and the divergent SCN in each echelon ($\Delta TVAmp_i$) (Figure 6), we can appreciate that differences between both SCNs increase upstream and become more important for higher values of the lead time variance. In fact, differences in BWE show an increasing exponential trend in the upstream direction of the SCN. Hence, in case of SCNs with a high number of echelons, the differences in the dynamic performance of the serial and the divergent SCN configurations are more critical. Furthermore, these differences are exacerbated by the lead time variability. Figure 7 shows how lead time variability impacts on the differences in BWE between the serial and the divergent SCNs. We can see how the differences in BWE is increased only in the last stage of both SCNs when the lead time variance moves from c.v.=0.00 to c.v.=0.25, but when the lead time variance is increased from c.v.=0.25 to c.v.=0.50, then the BWE is amplified all across the SCN following an exponential trend.

The analysis of the impact of the lead time variability on returns provides the following findings:

- *The global impact of returns on the BWE shows a high sensitivity to the lead time variance in case of a serial SCN, and a low sensitivity to the lead time variance in case of a divergent SCN.*
- *When returns are not allowed there are significant differences between the serial and the divergent SCNs. These differences exponentially increase upstream and are exacerbated by lead time variance.*

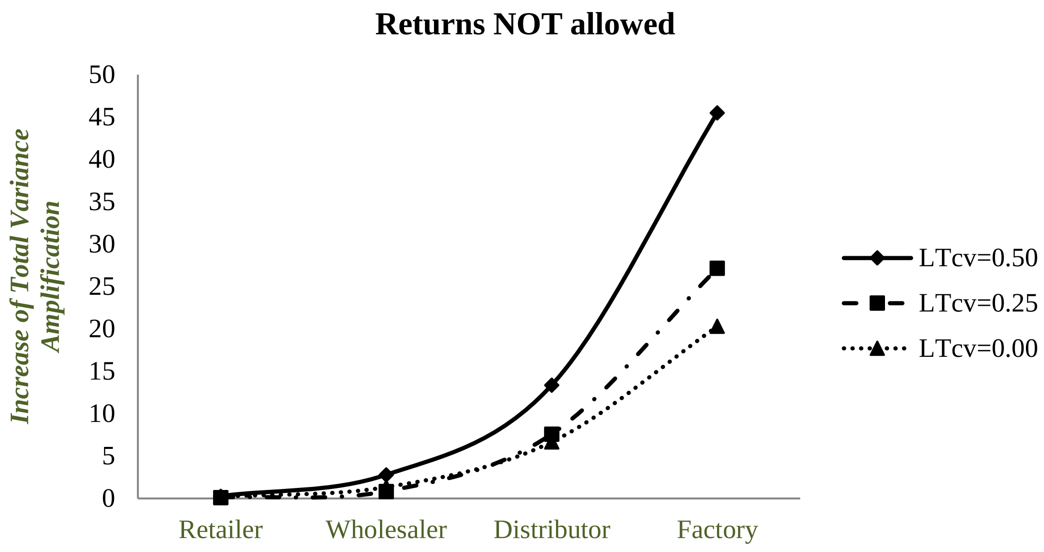

Figure 6. Differences in BWE between serial and divergent SCNs when returns are not allowed.

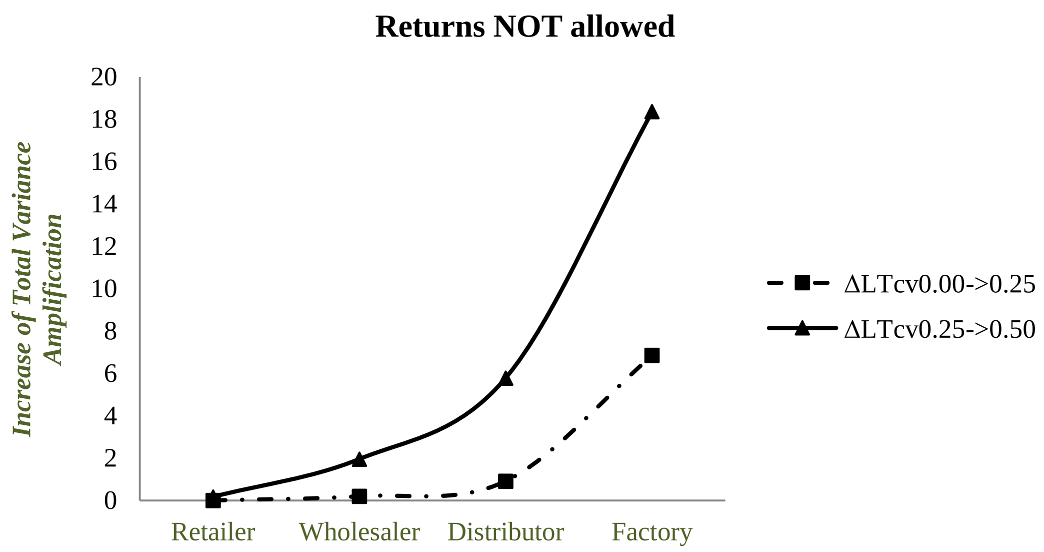

Figure 7. Impact of the lead time variability on the differences in BWE between serial and divergent SCNs when returns are not allowed.

The BWE and the compensation phenomena in divergent SCNs

The observed differences in performance between the serial and the divergent SCNs are caused by the so-called 'compensation phenomena' (Giard and Sali, 2013) that take place when two or more independent and identically distributed streams are added, and it is a well-known phenomenon in the risk pooling research field. Basically, if two streams $X_1(\mu, \sigma)$ and $X_2(\mu, \sigma)$ with identical average (μ) and standard deviation (σ) are added, the resultant stream X is given by $X(2\mu, \sqrt{2}\sigma)$, since the covariance between both streams is assumed to be zero in case of two independent streams. As a consequence, the coefficient of variation of the combined stream ($c.v._{(X)} = \frac{\sqrt{2}}{2}\frac{\sigma}{\mu} < \frac{\sigma}{\mu} = c.v._{(X1,X2)}$) is lower than the coefficient of variation of the individual streams, dampening the negative order events. Sucky (2009) demonstrate that, in this case, the resultant order-up-to policy leads to an attenuation of the relative variability of orders in each node of the divergent SCN.

The reduction in the number of negative orders caused by the compensation phenomena leads to the different performances observed between the serial and the divergent SCNs. In order to explain the relation between the compensation phenomena and the negative orders we focus on a particular case (lead time c.v.=0.50). Table 4 shows the negative orders and the variability of orders (indicated by their c.v.) for single nodes of each echelon in the serial and the divergent SCNs. In the serial SCN the standard deviation of orders placed by each echelon increases in the upstream direction, while the average of orders keeps constant. This phenomenon leads to increasing order variability in the upstream direction and thus, an increasing number of negative orders (see Table 4A).

This phenomenon is also observed in the divergent SCN (see Table 4B), but with an important difference: each node (with the exception of the retailers) receives demand from two nodes downstream (instead of one) and thus, since all demands are independent, the demand average received is the sum of the downstream demand averages, but the standard deviation of orders increases in a lower proportion due to the compensation phenomena. As a consequence, the orders placed by each node in the divergent SCN have lower variability and therefore they place less negative orders than the nodes of the same echelon in the serial SCN (see e.g. in Table 4A and 4B how a wholesaler in the divergent SCN places orders with c.v.= 0.81 and a total of 521 negative orders during the simulation time while a wholesaler in the serial SCN places orders with c.v.= 1.27 and a total of 1044 negative orders).

When negative orders are not permitted, orders are truncated to 0.0 and thus, a generic node of a serial SCN presents a higher number of truncated orders than the divergent SCN. Consequently, as the truncated order stream has lower variability (Chatfield and Pritchard, 2013), the serial SCN reveals a higher reduction in BWE than the divergent SCN when shifting from the returns allowed assumption to no-returns allowed assumption (see e.g. in Table 4C and 4A how the standard deviation of orders placed by the factory in the serial SCN decreases from 198.02 to 111.51 (43.65%) while in the case of the factory in the divergent SCN decreases from 539.37 to 483.63 (10.33%).

To sum up, we can summarize these finding as follows:

- *Negative orders depend on the coefficient of variation of the order pattern. In a divergent SCN, nodes place orders with a lower coefficient of variation than nodes in a serial SCN. Thus, divergent SCNs are characterised by less returns.*

(A) SERIAL SCN, RETURNS ALLOWED				
Single node in echelon *i*	**Orders Average**	**Orders *Std***	**Negative Orders**	**Orders c.v.**
Retailer	49.58	33.52	323	0.68
Wholesaler	49.57	63.01	1044	1.27
Distributor	49.55	118.36	1677	2.39
Factory	49.56	198.02	1992	4.00

(B) DIVERGENT SCN, RETURNS ALLOWED				
Single node in echelon *i*	**Orders Average**	**Orders *Std***	**Negative Orders**	**Orders c.v.**
Retailer	49.82	32.51	294	0.65
Wholesaler	99.43	80.27	521	0.81
Distributor	199.61	216.83	870	1.09
Factory	399.30	539.37	1132	1.35

(C) SERIAL SCN, RETURNS NOT ALLOWED				
Single node in echelon *i*	**Orders Average**	**Orders *Std***	**Negative Orders**	**Orders c.v.**
Retailer	50.69	33.26	0	0.66
Wholesaler	50.63	53.35	0	1.05
Distributor	50.59	80.56	0	1.59
Factory	49.64	111.51	0	2.25

(D) DIVERGENT SCN, RETURNS NOT ALLOWED				
Single node in echelon *i*	**Orders Average**	**Orders *Std***	**Negative Orders**	**Orders c.v.**
Retailer	50.22	33.50	0	0.67
Wholesaler	100.19	84.72	0	0.85
Distributor	200.57	208.10	0	1.04
Factory	386.16	483.63	0	1.25

Table 4. Negative orders placed by SCNs and its impact on the variability of orders.

The different impact of returns on transportation volume and capacity utilization in serial and divergent SCNs

Permitting returns will have an impact on transportation requirements (capacity) within the SCN (Chatfield and Pritchard, 2013) and, since transportation is a cost-intensive component of most SCNs, it needs consideration. Actually, the transportation volume increases by allowing returns, particularly at the upper echelons of the SCN, due to enabling transport in the upstream direction (two-way transport) as well as to the increased order variance due to the BWE (which is significantly aggravated by the ability to return goods). However, a divergent SCN with returns not allowed already faces a higher BWE than its serial SCN equivalent. Therefore, the transport lines of the divergent SCN do not face such an important increase in volume by allowing the return of goods since the returns are lower than in the serial SCN (see Table 4A and 4B) and the BWE increase is also lower (see Figures 4 and 5). In order to confirm this hypothesis, we present in Table 5 the increase in two-way transport volume along a single SCN link that results from allowing returns for the serial SCN and the divergent SCN. We show the results for the links comprised between the wholesaler and the external supplier, since the links below the wholesaler do not present notable increases. By looking at the results in Table 5 we can confirm that in fact, the increase in two-way transport due to returns allowance is much lower for the divergent SCN links than for the serial SCN links (see e.g. the maximum increase for the serial SCN, 222.17%, and the maximum increase for the divergent SCN, 53.53%).

Lead time c.v.	**SCN configuration**	**Percent increase in 2-way transport volume**		
		Whole-Dist	Dist-Fact	Fact-Supp
0.00	Serial	9.28	41.27	104.84
	Divergent	5.49	12.44	24.98
0.25	Serial	14.78	58.36	138.65
	Divergent	5.88	13.65	26.65
0.50	Serial	28.24	100.02	222.17
	Divergent	13.98	25.96	53.53

Table 5. Increase in two-way transport volume between node and upstream partner when returns are allowed vs. returns not allowed in serial and divergent SCNs.

There is a further implication that returns have on transport, more specifically on transport capacity. While allowing returns has the negative effect of increasing the transport volume, decisions to restrict returns can lead to potential reductions in transport capacity utilization because incoming demands are likely to be ‘‘lumpy’’ (one or more zero-sized orders separating positive orders). Lumpy demands means that adequate transportation capacity must be available to service large demands, but may sit idle for periods of time.

Here we address this important implication and its different impact in serial and divergent SCNs. In Table 6 we show the zero replenishment orders (Cannella et al., 2013), which account for the number of periods that a company does not place any order (nor positive or negative), for both SCNs. When returns are allowed, zero replenishment occurs randomly when the desired inventory level meets the current inventory position (no order placed). Consequently, the zero replenishment orders are very low for both SCNs and their values do not appear in Table 6. When returns are not allowed, the zero replenishment orders experiment a high increase due to the lumpy demands. Both SCNs experience a fast linear increase of zero replenishment orders in the upstream direction. They also show higher values of this metric for higher lead time variability. Finally, as it could be expected, the serial SCN shows higher zero replenishment orders than the divergent SCN, since the compensation phenomena reduces the number of zero replenishment orders placed by nodes of the divergent SCN.

A summary of findings regarding the different impact of returns on transportation observed in serial and divergent SCNs are:

- *The increase in transportation volume due to the two-way transport generated by the allowance of returns is significantly lower for the divergent SCN than for the serial SCN.*
- *The transportation volume increases with the lead time variance in both SCNs.*
- *Lumpy orders caused by the restriction of returns are lower for nodes of a divergent SCN than for nodes of a serial SCN.*
- *In both SCNs, intermittent orders increase as the lead time variance increases.*

Lead time c.v.	**SCN configuration**	**Zero replenishment when returns are NOT allowed**			
		Retailer	Wholesaler	Distributor	Factory
0.00	Serial	234	962	2011	2989
	Divergent	231.5	411	673	1068
0.25	Serial	301	1221	2442	3255
	Divergent	296.25	526.25	860.5	1174
0.50	Serial	396	1512	2732	3568
	Divergent	445.75	899.5	1455.5	1955

Table 6. Zero replenishment when returns are not allowed in serial and divergent SCNs.

7. Discussion

This section is dedicated to discuss the findings of this work. First we discuss the implications for managers and decision-makers. Finally we provide guidelines for SCN modeling purposes.

7.1. Managerial implications of returns in serial and divergent SCNs

In this section we discuss the managerial implications derived from our research. To do so, we also present an ad-hoc framework (Figure 8) which indicates how the performance metrics (i.e. BWE, transportation capacity and lumpy orders) are modified by the specific configuration of the SCN (divergent vs serial) and by the returns policy (returns vs no-returns). In this framework, arrows are oriented towards the direction of improving performance. The thickness of the arrows represents the magnitude of improvement. Finally, a two-way arrow means that there are no substantial improvements in either direction. The performance metrics shown in Figure 8 have several associated costs: the BWE is responsible of inefficiencies in terms of total costs increase, profitability deterioration, increased inventory holding costs, and increased cost of capital (Turrisi et al., 2013; Li and Liu, 2013); the transportation capacity has direct cost (trucks, ships, etc.); finally, the lumpy orders incur in fixed costs derived from the non-utilized transportation and/or production capacity. These costs are used in the following discussion.

A trade-off between costs associated to the BWE and two-way transport and costs associated to lumpy orders.

It can be noticed in Figure 8 that there is a generalized opposite trend between the directions of improvement of costs associated to the BWE and two-way transport capacity, and the directions of improvement of costs associated to lumpy orders. In general, due to the magnitude of the BWE, costs associated to this phenomenon should be higher than cost associated to lumpy orders. On the basis of this consideration, moving in the direction of improving BWE and two-way transport capacity would represent the most appropriate solution for the decision-maker. However, this condition strongly depends on the cost structure of a specific market sector. In fact, if fixed costs associated to the unused capacity for production and/or transportation of goods is very high, the negative impact of lumpy orders can undermine the benefit provided by the reduction of order variability and transportation capacity. In this context, managers may consider to increase the flexibility of the transportation/production capacity (for instance by using third-party logistics or sub-contracting production capacity). By doing so, it can be obtained a reduction of fixed costs and a consequently limitation of the negative impact of the intermittent demand phenomenon.

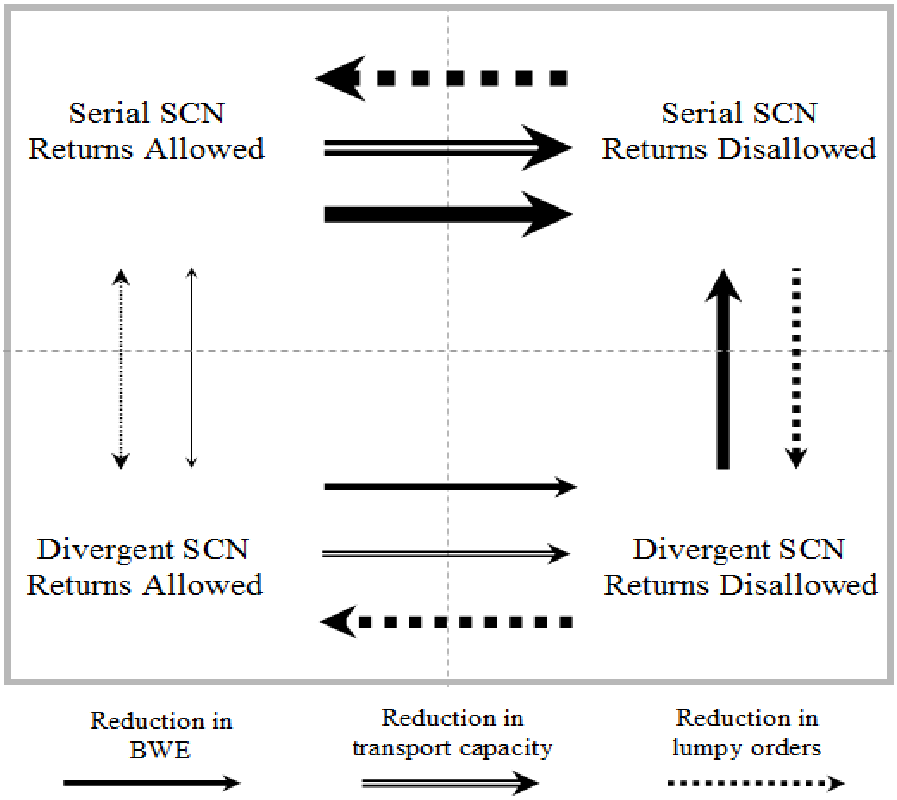

Figure 8. A summary of guidelines to improve performance.

The risk of returns policy on different SCN configurations

The adoption of a specific SCN configuration and a specific order policy are important managerial decisions. As shown in Figure 8, these decisions have to be based on a robust and context-related trade-off analysis between costs associated to the BWE and transportation capacity and costs associated to the lumpy demand. The risk related to the decision making on allowing/disallowing the return of goods policy is relevant. In fact, it can be noticed how the performance can strongly be modified (please see thickness of arrows) by shifting from the serial SCN with returns allowed to the same configuration with returns disallowed. On the contrary, the divergent configuration reveals a lower sensitivity to a modification of the returns policy. This configuration presents a higher resilience and robustness to the returns policy than the serial configuration. Thus, from a designer point of view, if we consider the returns policy as a tactical decision that may even change once the SCN is operating, the divergent SCN presents a lower risk than the serial SCN (it is less sensitive to costs involves with this decision). The risk related to the decision making on allowing/disallowing return of goods is undoubtedly lowered in a divergent SCN.

The above implications are exacerbated by the lead time variability. In a serial SCN, the lead time variability has a high impact on the variation of the BWE resultant from allowing/disallowing the return of goods. The BWE increases around 80% as the lead time variance shifts from c.v.=0.0 to c.v.=0.50 (see Figure 5). However, the same scenario in the divergent SCN results on a BWE increase of around 15%. Furthermore, there is also an increase in the two-way transport and lumpy orders caused by the lead time variability (see Tables 5 and 6). Consequently, we have shown evidences to consider the lead time variability as a key factor on decisions regarding the returns allowance/disallowance, and that enhance the robustness of the divergent SCN against the returns policy.

The impact of the returns policy on re-engineering the SCN

Now we discuss how shifting from a serial configuration to divergent configuration (and vice-versa) may impact the performance of the SCN under the adopted returns policy. The first issue to notice in Figure 8 is that changing the SCN configuration does not incur in costs associated to transport capacity. In fact, this cost is strictly associated to the returns policy. A second important implication is that, in case of returns allowed, the performance of the SCN (in terms of BWE and lumpy orders) is not significantly altered by changing the SCN configuration. Thus, in this case, the risk of the re-engineering process is very low. Nevertheless, if the SCN does not allow the return of goods, managers should consider that changing the configuration of the SCN will alter its current performance. More specifically, if costs derived from the lumpy orders (fixed production/transportation costs) are low, then changing from a divergent configuration to a serial configuration will improve the performance of the SCN and reduce costs. Otherwise, if costs derived from the lumpy orders are high, managers should balance these costs with those associated with the BWE in order to determine which configuration incur in lower costs.

Analogously to the previous managerial implication, the lead time variability plays an important role (when returns are not allowed): the benefits in terms BWE reduction obtained by changing from a divergent configuration to a serial configuration are higher as the lead time variability increases (see Figure 6). Nevertheless, we do not observe a clear tendency of improvement of the lumpy orders with the lead time variability, since the increases in both configurations are of a similar magnitude. From this viewpoint, as the lead time variability increases, it is more beneficial for managers of a divergent SCN to move to a serial configuration. Also, managers of a divergent SCN may try to reduce the lead time variability by implementing methodologies such as the "just-in-time" philosophy, obtaining performances closer to those of a serial SCN without changing the present configuration of the network.

7.2 Modeling implications of returns in serial and divergent SCNs

Here we discuss important modeling implications that can be derived from our findings, concerning the impact that two common modeling assumptions have on the accuracy of the results. Actually, assuming the return of goods in a SCN has several modeling advantages, such as the improvement of tractability by the elimination of truncated demand distribution (Chatfield and Pritchard, 2013). However, it has been shown that the return of goods has several associated costs and thus, returns are not always allowed in real SCNs. Also, SCNs have been often conceptualized as simple linear systems represented by a series of firms interacting through dyadic relationships (Cox et al., 2006). However, this linear conception, while it has several modeling advantages (such as mathematical tractability), it grossly oversimplifies and distorts the realities of modern SCNs (Hearnshaw and Wilson, 2013).

In this work, an important interaction between the two aforementioned modeling assumptions has been found: it has been shown that the impact of the returns allowance assumption on the order variance amplification depends on the SCN configuration. Therefore, assuming that a generic SCN can be modeled by a serial SCN has important limitations: if the return of goods is allowed (a modeling assumption that is essentially universal in the BWE literature) both models (i.e. serial and divergent SCNs) fit very well for this particular set of modeling assumptions (i.e. other kind of input demand such as "shock demand" results in notable differences between both models, Dominguez et al., 2014); however, in case of SCNs where the return of goods is not allowed, in general, the serial SCN model do not precisely account for the BWE found in divergent SCNs.

An exception occurs for divergent SCNs with very low number of echelons and low lead time variability: assuming that the differences in BWE between both SCNs exponentially increases with the number of echelons (see Figure 6), the divergent SCN can be approached by a serial SCN in case of low number of echelons (two or three echelons) and a low lead time variability (c.v.=0.0 to c.v.=0.25) with a low distortion of the results.

There is a second modeling implication related with the impact of returns on the BWE. Assuming that the returns allowance assumption has always an impact on the BWE, this impact is much lower in the case of divergent SCNs than in serial SCNs. Thus, in case of modeling a divergent SCN, it would be possible to assume the return of goods in order to simplify the model, since this assumption would have with a lower impact on the accuracy of the results (at least as compared to those in serial SCNs), particularly for short SCNs with low lead time variability (see Figure 4). In addition, a divergent SCN with a similar configuration to that of this paper but with a higher number of customers by each node would present, due to the compensation phenomena, a higher reduction of the number of negative orders placed by each node and thus, it would show a less sensitivity to the returns allowance assumption.

In short, it has been shown that, in addition to the distortion of the BWE caused by considering the two modelling assumptions independently, there is an important interaction between them that increases the errors introduced in the results obtained for the BWE, thus highlighting the importance of accurately modelling SCNs.

8. Conclusion

This research aims at analyzing how two common modelling assumptions in the BWE literature may impact on the accuracy of results obtained: (1) the assumption of allowing the return of the excess of goods and (2) the assumption of a serial configuration of the SCN. To do so, we perform a comparative analysis on the impact of returns on two different SCN configurations: a serial SCN and a divergent SCN. The SCNs have been modelled using a MAS-based SCN modelling tool (SCOPE) described in Dominguez and Framinan (2013). We quantify the BWE by measuring the total variance amplification at each echelon and the bullwhip slope. Aside, the negative orders placed by each node in both SCNs and the zero replenishment orders have been calculated to show the different behaviors of the analyzed chains and the different impact caused by returns in transportation. A full factorial set of experiments on three experimental factors (i.e. the configuration of the SCN, the returns assumption and the lead time variability) has been designed. ANOVA has been used to statistically analyze the significance of the results obtained from the simulation runs.

Our main contribution is the assessment of an important interaction between the return of goods and the configuration of the SCN. Indeed, the impact of returns on the BWE strongly depends on the configuration of the SCN. We have found that, due to the compensation phenomena that takes place when a company receives several uncorrelated demand streams (as it typically happens in divergent SCNs), the number of negative orders placed upstream are reduced as compared to that in a company within a serial SCN and thus, the divergent SCN is less affected by the returns allowance/disallowance. Particularly, the increase on the BWE caused by allowing the return of goods is drastically lower in the divergent SCN than in the serial SCN. Furthermore, the high sensitivity showed by the serial SCN to lead time variability on the returns issue is not observed for the divergent SCN, which shows a very low sensitivity to lead time variability. All this findings highlight the importance of testing the boundaries of modelling assumptions, since they may introduce important errors on the SCN model.

Also, important managerial implications have been discussed. Particularly, we discussed (1) the trade-off between costs derived from BWE and transport capacity and costs derived from the lumpy demand caused by neglecting the return of goods; (2) the risk of changing the returns policy on different SCN configurations; and (3) the impact of the returns policy on re-engineering the SCN.

This research has been limited to a comparison between a serial SCN and a divergent SCN. The results obtained could be extended by analyzing the implications of increasing the number of customers by each node (risk pooling) and analyzing the impact on the BWE and the negative orders placed by each node. Furthermore, our research is limited by the assuming that all demands are independent. A potential extension to this research is to determine how correlated demands (positive and negative correlated) may impact on the results obtained in this paper. Another important limitation is the absence of human behavior factors in our model, such as poor team decision-making, lack of sharing of customer demand information, and misperception of feedback, since there is a great interest on how human behavior, judgment, and decision-making affect SCN performance

(Croson and Donohue, 2006; Cantor and Macdonald, 2009; Cantor and Katok, 2012). A potential research proposal is to use laboratory experiments to analyze a similar problem to that of presented in this paper in order to assess how the mentioned human behavior interacts with the configuration of the SCN and returns.

Acknowledgements

We would like to thank the anonymous referees for their thoroughly revision and insightful comments on earlier versions of the paper. This research was funded by the Junta de Andalucía (Spain) [grant P08-TEP-03630 and Marie Curie Talentia], and by the Chilean National Science and Technology Research Fund [11140593].

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