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The impact of the supply chain structure on bullwhip effect

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Abstract: The aim of this paper is to study how the structural factors of supply chain networks, (i.e. the number of echelons, the number of nodes and the distribution of links) impact on its dynamics performance (i.e. bullwhip effect).To do so, we systematically model multiple structures according to a robust design of experiments and simulate such structures under two different market demand scenarios. The former emulates a stationary condition of the market, while the latter reproduce the extreme volatility and impetuous alteration of the market produced by the current economic recession. Results contribute to the scientific debate on supply chain dynamics by showing how the advocated number of echelons is not the only structural factor that exacerbates the bullwhip effect. In particular, under a sudden shock in market demand, the number of nodes and the divergence of the supply chain network affect the supply chain performance.

Keywords: supply chain management; multi-agent systems; simulation; demand amplification; complex supply chain; ANOVA.

1 Background and Motivation

Bullwhip Effect (BWE) refers to a progressive increase in order (demand) variance as order information passes upstream in a Supply Chain (SC) (Chatfield and Pritchard, 2013). BWE is the responsible of inefficiencies in terms of total costs increase, profitability deterioration, increased inventory holding costs, and higher cost of capital (Hassanzadeh et al., 2014; Li and Liu, 2013; Turrisi et al., 2013; Li, 2013). Nowadays, about two-thirds of firms are affected by the BWE (see e.g. Bray and Mendelson, 2012; Shan et al., 2013). Thus, BWE continues to be one of the most widely investigated phenomena in modern-day SC management research (Nepal et al., 2012; Zotteri, 2013).

Among the streams of research dealing with BWE, an important one has focused on showing its existence and on identifying its possible causes (Sucky, 2009). Among the different root causes that have been identified (please see Section n. 2), the ‘number of echelons’ or ‘number of channel intermediaries’ (Disney and Lambrecht, 2008) is considered a root cause that explicitly depends on the structure of the SC. In fact, there is a common agreement on the existence of a positive correlation between the reduction of the intermediate stages in the SC and the reduction of the BWE (Disney et al., 2004; Paik and Bagchi, 2007; Disney and Lambrecht, 2008; Bottani and Montanari, 2010; Yang et al., 2011; Sodhi and Tang, 2011). For this reason, the reduction of channel intermediaries and the adoption of reduced SCs (such as the direct channel, or “the Dell model”) (Disney and Lambrecht, 2008) have been promoted as effective strategies to mitigate BWE.

However, SCs are usually networks or global networks (Corominas, 2013). Hence, the number of echelons only represents an indicator of the structure of the Supply Chain Network (SCN). The structure of the SCN, defined as the arrangement of the various SCN nodes (Giard and Sali, 2013) is a critical decision for managers that is becoming increasingly complex (Von Massow and Canbolat, 2014). In general, three main factors determine the structure of the SCN and consequently also the material flow from the raw materials stage to the final customer stage (Suchy, 2009): (1) the number of echelons, (2) the number of facilities at each echelon, and (3) the number of links between the locations. These elements may have a dramatic effect in terms of cost, customer satisfaction, ability to respond to market changes, and ability to innovate and bring new products to the market (Von Massow and Canbolat, 2014).

Among these three elements, published works have only explicitly investigated the impact of one of them, i.e. the number of echelons in the BWE. Probably the reason is that most scientific works dealing with the BWE are confined to the classical single-echelon, dyadic, or serially-linked configurations (Sucky, 2009; Bhattacharya and Bandyopadhyay, 2011; Giard and Sali, 2013). In these configurations it is not possible to assess the impact of the aforementioned structural factors on the BWE, with the mere exception of the serially-linked configuration, where it is possible to quantify only the effect of the number of echelons. However, recent studies (see e.g. Dominguez et al., 2014 and Dominguez et al., 2015) show how different SCN configurations with the same number of echelons may have different SCN performances. Thus, there is a need to assess the impact of all SCNs structural factors on performance.

To the best of our knowledge, the potential relation between key structural factors and the BWE is almost unknown, with the exception a few anecdotic evidences, which, however, do not provide information on the impact of the different factors in the BWE (see e.g. Sodhi and Tang, 2011). Motivated by these considerations, the aim of this paper is to quantify the impact of the SCN structure (i.e. the number of stages, the number of facilities at each stage, and the number of links between the locations) on the BWE. To do so, we simulate the dynamic response of several configurations in one of the most widely used SCN typologies in real businesses: the divergent SCN (Beamon and Chen, 2001). This configuration is characterized by a tree-like structure, where every stock point in the system receives supply from exactly one higher level stock point, but can supply to one or more lower level stock points (Hwarng et al., 2005). Consumer-oriented industries, such as cell phone manufacturers, appliances, electronics, and computer industries often adopt this typology of SCN (Hung, 2011). To identify the structural factors having a statistically significant impact on the BWE, we perform a full factorial set of experiments by varying these factors under identical SCN operational parameters (e.g. lead times, safety stock factors, demand forecast factors, etc.). Furthermore, in order to increase the robustness of the analysis, we adopt the framework for studying the BWE proposed by Towill et al. (2007). More specifically, we adopt two input demand patterns, i.e. the variance lens and the shock lens. The former aims at inferring on the performance of SCNs for a stationary input demand. The latter aims at inferring on the performance of SCNs for an unexpected and intense change in the end customer demand. This type of demand has been adopted in theoretical BWE studies in order to model the extreme volatility and impetuous alteration of the market produced by the current economic recession (Cannella et al., 2014a). The simulation platform used in our work is SCOPE (Domínguez and Framinan, 2013), a multi-agent system (MAS) based software platform for the simulation of complex SCNs.

Results for the variance lens show that the factor 'number of echelons' has a high impact on the BWE while the number of nodes and the divergence of the SCN have a low impact, which is in line with the results found by other authors. However, for the shock lens, in addition to the number of echelons, the number of nodes and the divergence of the SCN also have a significant impact on the BWE. More specifically, as the levels of the structural factors increase, the BWE increases with different trends. In fact, BWE quickly (exponentially) increases as the SCN shifts from a low number of echelons to a high number of echelons, but the increase is smoother with the number of facilities in each echelon and with the divergence of the SCN. Also, there is an important interaction between the number of echelons and the divergence of the SCN in this scenario. Finally, we prove how BWE is very sensitive to the structure of the SCN under a sudden shock in customer demand.

The rest of the paper is organized as follows: Section 2 presents a literature review. Section 3 describes the structural elements of SCNs and the inherent structural characteristics of divergent SCNs. In Section 4 the SCN model is presented. Section 5 briefly describes the software platform used for computer simulation. Section 6 includes the design of experiments and Section 7 shows the results numerical analysis. Finally, Section 8 presents the implications of the research and Section 9 contains the conclusions and future research lines.

2 Literature Review

The identification of the root causes of the BWE is an important stream in SCN literature and has long been of interest for industrial practitioners and academics (Lin et al., 2014b). In this context it is possible to distinguish two schools of thought, i.e.: the System Thinking school, and the Operations Managers' school (Miragliotta, 2006). The former, focused on the behavioral causes, is mainly interested in the ''systemic'' nature of the SCN, reflecting a holistic perception of the causes of the BWE. The Operations Managers' school focuses on the operational causes. Thus, it concentrates on single elements rather than on the whole system. Both schools have largely contributed in suitably defining causes and remedies for the BWE. Thanks to these efforts, during the last decades several classification frameworks have been proposed. Undoubtedly Lee et al. (1997) provided the seminal work that defined the BWE and identified the well-known five causes (Disney and Lambrecht, 2008; Zotteri, 2012). A further relevant framework was proposed by Geary et al. (2006). The authors identified 10 published causes of BWE, based on the works by Mitchell (1924), Wikner et al. (1992), and Lee et al. (1997).

Bhattacharya and Bandyopadhyay (2011) identify 19 causes, 16 of them operational and 3 behavioral. Operational causes include demand forecasting (Syntetos et al., 2009; Trapero et al., 2012), order batching (Potter and Disney 2006), price fluctuation (Ma et al., 2013; Lu et al., 2012), rationing and shortage gaming, lead time, inventory policy, replenishment policy, improper control system (Disney and Towill 2003; Syntetos et al., 2011), lack of transparency (Cannella et al., 2014b; Hussain et al., 2012), number of echelons (Disney et al., 2004; Paik and Bagchi, 2007), multiplier effect, lack of synchronization (Ciancimino et al., 2012), misperception of feedback (Gonçalvez et al., 2005), local optimization without global vision (Disney and Lambrecht, 2008), company processes (Holweg et al, 2005, Cannella et al. 2014c) and capacity limits (Crespo-Marquez, 2010). The behavioral causes cover neglecting time delays in making ordering decisions (Wu and Katok, 2006), lack of learning and/or training (Akkerman and Voss, 2013, Bruccoleri et al., 2014), and fear of empty stock/customers' baulking behavior (Croson and Donohue, 2006; Lin et al., 2014a). A recent classification of the BWE causes is provided by Lin et al. (2014b).

However, all previous works have not considered the different factors of SCN structure as potential drivers of the BWE, with the mere exception of one factor: the number of echelons. To the best of the authors' knowledge, the first framework that explicitly considers the SCN structure as a root cause of the BWE is Giard and Sali (2013). The authors perform an extended literature review, classifying approximately 50 articles published in major journals. In their work, authors identify 7 root causes, being the "SCN structure" one among them. Furthermore, they classify each paper according to the adopted SCN configuration. More specifically, they identify the following 5 configuration:

- ✓ *Dyadic*: single customer with a single supplier.
- ✓ *Serial*: a succession of nodes in which each node has at most one predecessor and one successor.
- ✓ *Convergent* (assembly): are assembly-type configurations in which each node in the SCN has at most one successor, but may have any number of predecessors.
- ✓ *Divergent or arborescent* (distribution): if each node has at most one predecessor, but any number of successors.
- ✓ *General*: is a general configuration that does not fall into any of the preceding configurations.

Table 1 reports an adapted version of literature effort provided by Giard and Sali (2013). By analyzing this table, it can be noted that most studies have exclusively adopted the classical serially-linked SCN (Bhattacharya and Bandyopadhyay, 2011). Other studies have adopted the convergent configuration. However, none of these works explores the SCN structure as a potential driver for the BWE. Analogously, the few studies adopting the divergent configuration do not focus on the relation of between the structural factors and the BWE.

According to Giard and Sali (2013), the only two works considering the SCN structure as a potential driver of the BWE are the framework of Geary et al. (2006) and the simulation study of Wangphanich et al. (2010). The framework of the former authors merely identifies the well-known "number of echelon" as a root cause of the BWE. Analogously, the latter authors, in their analysis of a multi-product SCN do not report any insight on how these structural factors influence the performance of the SCN. In fact, they focus on the dynamic response of a fixed SCN structure: a 3-echelon divergent SCN under different order policies and information sharing strategies. This finding stimulates the need of further structured studies on the relation between the structural factors of the SCN and BWE.

Table 1. SCN configuration and root causes (adapted from Giard and Sali, 2013).

	SCN Configuration					Causes of the BWE									
Articles	Dyadic	Serial	Divergent	Convergent	Network	Reliability of Forecasts	SC Structure	Demand Variability	Pricing Policies	Shortage Risk	Lot-sizing Policy	Lead Time Variability	Control Model	Shared Information	Human Factor
Agrawal et al. (2009)	X					X								X	
Bailey and Francis (2008)		X												X	X
Balan et al. (2009)		X				X		X					X		
Bayraktar et al. (2008)	X					X						X			
Ben-Tal et al. (2009)		X											X		
Campuzano et al(2009)		X										X			
Cachon and Fisher (2000)			X										X	X	
Cachon and Lariviere (2001)	X														
Cachon et al. (2007)		X						X	X						
Chan et al. (2004)					X										
Chatfield et al. (2004)		X				X						X		X	
Chen et al. (2006)	X														
Chen and Lee (2009)	X							X					X	X	
Cheng (2009)		X											X	X	
Childerhouse et al. (2008)		X				X		X		X	X	X	X		
Croson and Donohue (2005)		X												X	
Dejonckheere et al. (2002)	X					X									
Dejonckheere et al. (2003)	X					X							X		
Dejonckheere et al. (2004)		X				X							X	X	
Disney and Towill (2003)	X												X		
Özelkan and Çakanyildirim (2009)	X	X							X						
Ganesh et al. (2008)	X														
Geary et al. (2006)						X	X	X	X	X	X	X	X	X	X
Huang et al. (2005)	X														
Jung et al. (2007)					X										
Kelepouris et al. (2007)			X			X						X	X		
Lau et al. (2005)	X														
Lau et al. (2004)			X												
Lee et al. (1997)						X			X	X	X				
Lee et al. (2004a)						X			X	X	X				
Lee et al. (2004b)						X			X	X	X				
Li and Gao (2008)	X														
Li and Zhang (2008)			X												
Liu et al. (2009)		X													
Moinzadeh (2002)			X												
Nienhaus et al. (2006)		X													X
O'Donell et al. (2009)		X						X	X						
Ouyang (2007)		X												X	
Ouyang and Li (2010)					X										
Pereira et al. (2009)		X						X							
Ryu et al. (2009)		X												X	
Springer and Kim (2010)	X							X							
Sucky (2009)			X				X								
Thonemann (2002)			X											X	
Viswanathan et al. (2007)		X													
Wang et al. (2005)		X				X		X					X	X	
Wangphanich et al. (2010)					X	X	X						X		
Wong et al. (2009)			X												
Wright and Yuan (2008)		X				X							X		
Wu and Cheng (2008)		X													
Yee (2005)		X													
Zhang (2004)	X					X									
Zhao and Xie (2002)			X												

3 The Divergent SCN configuration

This work focuses on the analysis of divergent SCNs. In this section, the structural elements of a SCN are described, and then, the inherent characteristics/constraints of this specific configuration are formalized. The SCN structure arises from the connected facilities that work together in order to supply products or services. In a SCN, each link represents the flow of materials and information that makes possible the functions of procurement, processing (or manufacturing), storage and distribution. For any given SCN, each functional level comprises an echelon, and there may be numerous facilities within each echelon (Beamon and Chen, 2001). This definition of the SCN structure is in accordance with the growing literature on complex networks, in which the SCN is modeled as a network by a set of "nodes" that represent autonomous business units (firms or facilities), and a set of "connections" (links) that link these firms together in demand-supply relationships for the purposes of creating products or services (Hearnshaw and Wilson, 2013; Gerschberger et al., 2012; Wen et al., 2012; Kim et al., 2011; Li et al., 2010a; Li et al., 2010b; Li et al., 2009; Choi et al., 2001). Hence, in line with the literature, we formalize the structure elements of a SCN as follows:

- ✓ Echelons: the number of echelons is denoted by $i \in (1, E)$, with E the total number of echelons in the SCN. Echelons are numbered downstream starting from the suppliers, which are in echelon i = 1.
- ✓ Nodes: a generic node j in echelon i is denoted by n_{ij}. The number of nodes in a specific echelon i is N_i. The total number of nodes in the SCN is: $\sum_{i=1}^{E} N_i = N$.
- ✓ Links: a link between nodes n_{ij} and $n_{i'j'}$ is denoted by $l(n_{ij}, n_{i'j'})$ and the total number of links is L. There are two commonly used indicators to measure the degree of linkage in a SCN, namely the connection degree and the cluster coefficient (see e.g. Wen et al., 2012; Kim et al., 2011; Xuan et al., 2011; Li et al., 2010a; Barbási et al., 2002) . The connection degree D_{ij} is defined as the sum of a node's links (Li et al., 2010a). The number of suppliers linked with node n_{ij} is the in-degree (di_{ij}), and the number of customers linked with a node n_{ij} is the out-degree (do_{ij}) (Kim et al., 2011; Xuan et al., 2011). The sum of the in-degree and the out-degree is the connection degree: $D_{ij} = di_{ij} + do_{ij}$. The clustering coefficient C is the probability that two nearest neighbors of a node are also nearest neighbors of one another (Li et al., 2010a). Given node n_{ij} linked to k_i other nodes in the system, if these k_i nodes form a fully connected clique, there are $k_i(k_i - 1)/2$ links between them. Let us denote by λ_i the number of links that connect the selected k_i nodes to each other. The clustering coefficient for node n_{ij} is then $2\lambda_i/k_i(k_i - 1)$ (Barbási et al., 2002).

The number of nodes, the number of echelons, and the structure of the material and information flows (links) has given rise to a structural classification scheme of SCNs based on the material relationship between nodes (Beamon and Chen, 2001). Up to now, most of the literature on the BWE topic has analyzed the classical serial SCN (see Sections n.1 and 2). In this SCN, the number of nodes in each echelon is limited to one ($N_i = 1$), and hence, the number of nodes and echelons in the SCN is the same ($N = E$). The connection degree is also limited: each node supplies to one node in the successor echelon ($do_{ij} = 1$) and it is supplied by one node in the predecessor echelon ($di_{ij} = 1$), thus limiting the total number of links to $L = N - 1$. Summing up, the structure of the serial SCN configuration is very restrictive: by selecting the quantity of one of the structural elements above mentioned (echelons, nodes or links), the SCN structure is defined, thus limiting the analysis of the influence of the SCN structure on the BWE to the number of echelons.

In this paper, we focus on the divergent SCN configuration, which is less restrictive than the serial configuration. The inherent structural restrictions of divergent SCNs are described and formalized next:

1. The number of nodes in each echelon is equal or greater than the number of nodes in its predecessor, i.e.: $N_i \geq N_{i-1}$. Furthermore, in order to exclude the serial SCN, the total number of nodes is constrained to $N \geq E$+1.
2. A node n_{ij} can supply to any number of nodes in the successor echelon ($do_{ij} \geq 1$), but can be supplied only by one node from the predecessor echelon ($di_{ij} = 1$) (Beamon and Chen, 2001).
3. Nodes in the same echelon are not linked. Hence, the network clustering coefficient *C* is zero. This is consistent with most cases in real-world SCNs (e.g. divergent SCN), that is, entities in the same echelons normally have no demand-supplier relations (Li et al., 2010a). This constraint, together with the previous restriction, limits the total number of links to the total number of nodes minus one: $L = N - 1$.

By observing the above constraints, it can be noted that *N* is greater than *E* in divergent SCNs and thus, echelons are allowed to contain more than one node. Furthermore, for a given *E*, there is no upper bound for *N*. Thereby, any distribution of nodes across the SCN satisfying restriction (1) is allowed. In addition, nodes can supply to any number of nodes downstream, as indicated by restriction (2). Hence, there might be nodes with a high connection degree while others with low connection degree, resulting in SCNs with different degree distributions. In a first attempt to measure the impact of the SCN structure on the BWE, in this paper we do not consider the connection degree as a factor, and for this reason, the divergent SCNs under analysis have homogeneous degree distributions: all nodes in the same echelon have similar connection degrees. Instead, we focus on the number of echelons, the number of nodes, and the distribution of links (or nodes) along the SCN.

Given a SCN characterized by [*E*, *N*], there are multiple configurations depending on how nodes are distributed over the echelons. SCNs with different configurations may have different behavior in terms of BWE. To characterize the different configurations, we propose a "divergence factor" (*divF*), defined as the standard deviation of the number of nodes across the echelons of the SCN related to the average number of nodes in each echelon (*N/E*) (equation (1)). If nodes are uniformly distributed (i.e. identical number of nodes in each echelon), the SCN is characterized by a serial topology (see Figure 1), thus obtaining a *divF* of zero. On the contrary, a divergent SCN, with an increasing number of nodes in consecutive echelons, would present a *divF* greater than zero. Furthermore, we can distinguish between SCNs with lower *divFs* and SCNs with higher *divFs* (see Figure 1). The former are SCNs with a density of nodes close to the average (*N/E*) in each echelon and thus, characterized by echelons with similar importance in the supply path to the end customers (i.e. all nodes supplies to more or less the same quantity of nodes downstream). The latter are SCNs in which the first echelons have a low density of nodes and the last echelons (retailers) have a high density of nodes. These SCNs are characterized by echelons with a critical importance in the supply path to the end customers (i.e. a few nodes supplying a high number of nodes downstream).

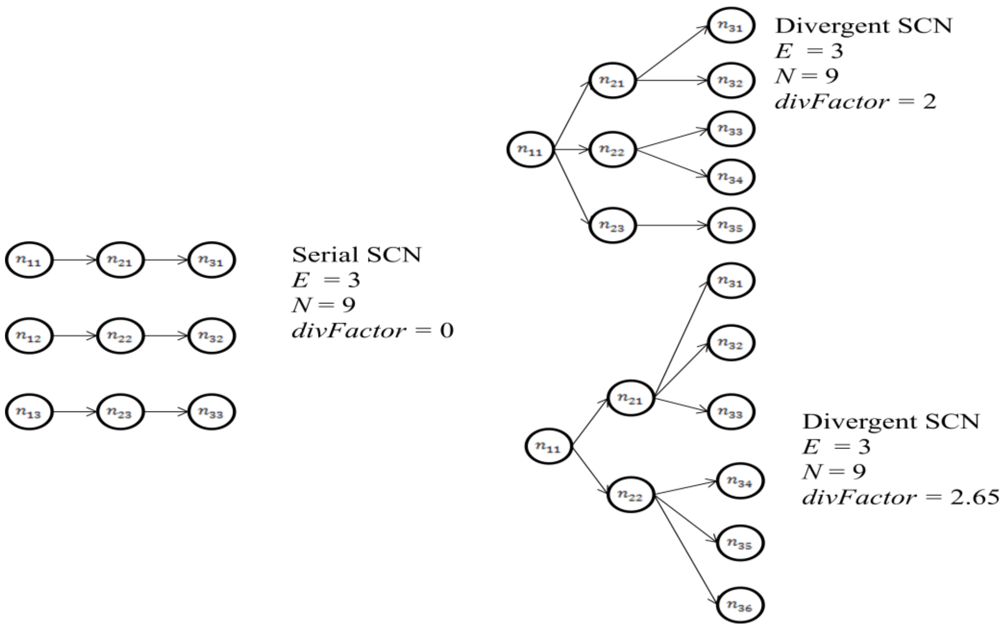

Figure 1. Three different SCNs configurations with the same *E* and *N*, and an increasing *DivF*.

$$divF = \sqrt{\sum_{i=1}^{E} \frac{(N_i - N/E)^2}{E-1}} \tag{1}$$

4 SCN Model

Since the research is focused on the structure of the SCN, parameters related to the operation of the SCN (i.e. operational parameters) are held constant in this research. We have based our SCN model on that of Chatfield et al. (2004), a much cited work in BWE research. The main characteristics of the SCN model, which are common to all SCNs modeled, are summarized next:

- **External Supplier**. Factories place orders to an outside supplier.
- **Customers.** There is one different customer placing orders to each node in the last stage of the SCN. Customers' demands are independent and identically distributed, following a normal distribution with mean μ_{O_C}, estimated by $\overline{D}_{O_C}$, and variance $\sigma^2_{O_C}$, estimated by $s^2_{O_C}$. Customers do not fill orders.
- **Lead Times**. Lead times (L) are deterministic. 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. All nodes in the SCN use the (R, S) policy (where R is the review period and S is the order-up-to level), and the time period of protection is L+R.
- **Lead-Time Demand**. Let X^t_{ij} be the demand received by node j in stage i during protection period L+R. Then X^t_{ij} has mean μ_X (estimated by $\bar{X}^t_{ij}$), and variance σ^2_X (estimated by $s^2_{X^t_{ij}}$). Denoting by D^{t+k}_{ij} the demand received by node j in stage i at time $t + k$, we obtain X^t_{ij} for an order placed at time t by the convolution:

$$X^t_{ij} = \sum_{k=0}^{L+R} D^{t+k}_{ij} \tag{2}$$

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

$$S_{ij}^t = \bar{X}_{ij}^t + z s_{X_{ij}^t} \tag{3}$$

Thus, at the beginning of every period t, each node j in stage i will place an order to raise or lower the inventory position to S_{ij}^t, using the safety factor z. To update the S_{ij}^t level, a node *j* in stage *i* can access to the demand data from previous periods (used to forecast the expected demand at time period *t*, $\bar{D}_{ij}^t$, and its variance, $s_{O_{ij}^t}^2$), and with this information it generates forecasts of lead-time demand of mean $\bar{X}_{ij}^t$ and variance $s_{X_{ij}^t}^2$, as indicated in (4) and (5), respectively:

$$\bar{X}_{ij}^t = (L + R)\bar{D}_{ij}^t \tag{4}$$

$$s_{X_{ij}^t}^2 = (L + R)s_{O_{ij}^t}^2 \tag{5}$$

To estimate $(\bar{D}_{ij}^t, s_{O_{ij}^t}^2)$, each node uses a *p*-period moving averages (*MA*(*p*)) and a *p*-period moving variances (*MV*(*p*)).

- **Reverse Logistic**. With the exception of end customers, all SCN nodes are allowed to return goods. Thus, replenishment order sizes may be negative.

- **Scope of Information**. Each node's SCN knowledge-base is derived from the incoming demand flow coming from downstream partners and the outgoing flow of orders being placed with the upstream partner.

- **Timing of Actions**. In each time period, each node (in a sequence from downstream stages to upstream stages, and randomly for nodes in the same stage) performs the following sequence of actions:

  1. Update the order-up-to level (S_{ij}^t) using the forecast calculated in the previous period.
  2. Place an order to raise or lower the inventory position to S_{ij}^t.
  3. Receive products from the upstream node.
  4. Receive new orders from downstream nodes and satisfies demand.

5. Calculate a new forecast to be used in the next period.

5 Computer simulation

The numerous interactions between entities as well as the characteristics of nonlinearity, dynamics, uncertainty, etc. in SCNs make it challenging to analyze and to predict their responses over time (Li et al., 2010a,b). In addition, owing to these characteristics, SCNs are recognized as complex adaptive systems (Surana et al., 2005; Pathak et al., 2007; Wang et al., 2008; Chen, 2012). One of the most used approaches in SCM is analytical modeling, such as control theory, linear programming, integer programming, or mixed integer programming. Unfortunately, analytical models are unable to cope with the complex adaptive systems' features effectively (Long et al., 2011). Simulation has rapidly become a significant methodological approach to theory development in the literature focused on strategy, organizations and SCN management, due to its ease for modeling and its capability of handling the dynamics and stochastic behavior of the inter-related SCN processes (Chan and Prakash, 2012). It has proven to be a useful tool to achieve holistic improvements and to go beyond the own factory gate, helping companies to understand that the optimal state for their own company can only be found by considering the effects of company's behavior and collaborating with their up- and downstream SCN members (Holweg and Bicheno, 2002). Furthermore, simulation models are useful for measuring BWE (Min and Zhou, 2002). Particularly, MAS-based distributed simulation turns to be one of the most effective tools to model and analyze SCNs because there is a natural correspondence between SCN participants and agents in a simulation model (see Swaminathan et al. 1998, Chatfield et al. 2001, Julka et al. 2002, Dong et al. 2006, Govindu and Chinnam 2010, Long et al. 2011, Chatfield et al. 2012, and Chatfield 2013 among others).

SCNs have been modeled using SCOPE (Domínguez and Framinan, 2013), a MAS-based software platform for the simulation of complex SCNs. SCOPE allows an easy modeling of real-scale SCNs in which each company can be set up with different policies and parameters for the different business functions. By running the models, the user can gather all data related to individual or global performances. The MAS paradigm allows flexible configurations of the system, and SCOPE has exploited this valuable feature to permit modeling and simulating a wide variety of SCN configurations.

SCOPE uses a two-layer framework for modeling the SCN. The first layer is composed of a collection of generic agents (Enterprise Agent), each one modeling a company in the SCN and interacting between themselves. The second layer includes a collection of nine different functional agents, which have been selected considering the Supply Chain Planning Matrix of Stadtler (2005). These agents are: Demand Fulfilment Agent, Demand Forecast Agent, Master Planning Agent, Production Planning Agent, MRP (Material Resource Planning) Agent, Scheduling Agent, Source Agent, Make Agent and Deliver Agent. Depending on the role played by the company, the Enterprise Agent will be composed of different combinations of these functional agents.

The simulator was implemented in Java and uses Swarm (a well-known software platform for agent-based system development). It has been conceived to be open-source to help practitioners in their research. Its modular design makes easy to add new functions and behaviors to the agents and hence, it can be easily customized. SCOPE has been validated by contrasting the results obtained from the simulations that have been carried out on a SCN previously modeled by other authors. More specifically, in Dominguez and Framinan (2013), a four-stage serial SCN has been modeled and the results (amplification of the standard deviation of orders) obtained by SCOPE are compared with those provided by Chen et al. (2000), Dejonckheere et al. (2003) and Chatfield et al. (2004). For further information on SCOPE and on the validation process please see Dominguez and Framinan (2013) and Dominguez et al. (2014).

6 Design of experiments

To analyze the impact of different levels of the structural factors on the BWE, we design a full factorial set of experiments, where different levels of each factor are tested, allowing us to obtain information about the main effects of each factor and its interactions with the rest of the factors, yielding conclusions that are valid over a wide range of experimental conditions.

The chosen design of experiments is summarized in Table 2. In order to assess the impact of the structural factors on BWE, three levels have been considered for factors *E* and *N* (low, medium and high), and two levels for *DivF* (low and high). SCNs with a low value of *E* are small SCNs with a low number of intermediaries (products require low processing and are delivered almost directly to customers, e.g. Provider, Factory, Retailer and Customer). On the contrary, SCNs with higher *E* values are those with a high number of intermediaries (typically big distribution networks delivering products worldwide). SCNs between those levels of echelons belong to the medium level. Values of *N* are proportional to the number of echelons. SCNs with higher *N* values are those with a high number of companies in each level and, in the end, high number of retailers, thus having a better geographical availability to customers. On the contrary, SCNs with lower *N* value present a low number of retailers, while those between low and high *N* belong to the medium level. *DivF* value is restricted for a given combination of *E* and *N*, having a lower bound (*Min*) and an upper bound (*Max*) (see Table 2). Values belonging to the first half of the interval [Min, Max] correspond to the low level of *DivF*, and values belonging to the second half correspond to the high level of *DivF*.

The factorial design with these levels requires 18 observations (3x3x2). The design of experiments carried out by other authors is often limited to fixed values of each level (see e.g. Hussain et al., 2012; Patel and Jena, 2012; Bottani and Montanari, 2010; Paik and Bagchi, 2007; Khumwan and Pichitlamken, 2007; Chatfield et al., 2004). In order to obtain more general results, we use an interval of possible values for each level instead of a fixed value (see Table 2). In each replication, the values for each level of the factors are chosen randomly among all possible values within the interval. The intervals for each factor have identical sizes. Due to the high variability introduced by the use of these intervals of values for each factor instead fixed values, a high number of replications (150) has been run for each combination of factors, obtaining a total of 2,700 simulation runs.

Table 2. Full Factorial Set of Experiments

Structure Factors	**Levels and Intervals of values**
E	Low: $E \in [2-4]$; Medium: $E \in [5-7]$; High: $E \in [8-10]$
N	Low: $N \in [E-3E]$; Medium: $N \in [3E-6E]$; High: $N \in [6E-9E]$
$divF$	Min: $\sqrt{\frac{\left(N-floor\left(\frac{N}{E}\right)*E\right)^2}{E}}$; Max: $\sqrt{\frac{(E-1)*(1-\frac{N}{E})^2+(N-E+1-\frac{N}{E})^2}{E-1}}$; Low: $divF \in [Min, Min+\left(\frac{Max-Min}{2}\right)]$; High: $divF \in [Min+\left(\frac{Max-Min}{2}\right), Max]$

In order to increase the robustness of the BWE analysis, we adopt two different perspectives or “lenses” taken from the framework proposed by Towill et al. (2007). In the variance lens scenario, the demand pattern is the same as in Chatfield et al. (2004), i.e. demand follows a

$N(50, 20^2)$ distribution. In the shock lens scenario, a $N(50, 20^2)$ distribution suffer an average increment of 100% in a certain time period (see Table 3), turning into a $N(100, 20^2)$. These demand patterns are applied to every customer in the SCN. A set of the above mentioned 2,700 experiments have been run using the variance lens and another identical set have been run suing the shock lens, making a total of 5,400 experiments.

To isolate the effects of the structural factors on the BWE, other characteristics which are known to be BWE initiators, with the exception of the stochastic demand and its forecast, are not included in the SCN model. The selection of the parameter's values of the SCNs has been done according to Chatfield et al. (2004) (see Table 3). The simulation horizon is set to 900, with the first 400 periods used as a warm-up used to set up the system.

Table 3. Model's parameters.

P	Periods of forecasting	15
Z	Safety factor	2 (service level of 97.72%)
R	Review interval	1
L	Lead time	4
simTime	Simulation time	900
wUP	Warm-up	400
vL	Variance Lens	$N(50, 20^2)\ \forall\ t$
sL	Shock Lens	$N(50, 20^2)$ $t \in$ [0-549] $N(100, 20^2)$ $t \in$ [550-900]

In order to measure the BWE, we found several key performance indicators in the literature. The order rate variance ratio, first proposed by Chen et al. (2000) and often computed as the ratio of the order variance in a generic node and the order variance of the customer, is by far the most widely used indicator to detect the BWE (Cannella, 2014; Cannella et al., 2013). This metric is appropriate in situations where customer demand is stochastic, following a probability distribution, e.g. the variance lens scenario (Towill et al., 2007). However, as we also consider the shock lens scenario, a peak of orders metric has been chosen to measure the extreme swings in order patterns (Towill et al., 2007). Since the dynamics of the order pattern at the first echelon presents the "worst-case" scenario, the BWE registered at this echelon is analyzed (Hussain et al. 2012). Hence, we measure the BWE as the maximum change in orders placed by nodes in the first echelon. In order to obtain this measure, we have to note that, in a divergent SCN, echelons are allowed to contain more than one node, and thereby it is necessary to find an aggregate measure. Therefore, the sum of orders of every node j in the echelon i (O_{ij}^t) are considered, resulting in an aggregate order pattern for the echelon i: $AO_i^t = \sum_{j=1}^{n_i} O_{ij}^t$. Thus, we formalize the peak of orders in echelon one as follows:

$$PeakO_1 = \max(AO_1^t) - \min(AO_1^t)\ \forall t \in [wUP, simTime] \tag{6}$$

7 Results and numerical analysis

In order to identify the statistically significant factors, two ANOVAs are performed separately for the variance lens and the shock lens, and both scenarios are analyzed. The independent variables are factors *E, N,* and *DivF*, while the dependent variable is the level of order instability at the first echelon ($PeakO_1$) in the SCN.

Systems are often driven primarily by some of the main effects and low-order interactions, say, two-factor interactions, while higher order interactions are negligible for all practical purposes (Hinkelmann and Kempthorne, 1994). ‘Main effect’ refers to the effect of a structural factor on the BWE when the factor’s value changes from one level to another. Interaction refers to the effect of changes in a particular structural factor value as the values of another factor change. Since high-order interactions are often minimal, only information on the main effects and low-order interactions is analyzed for each scenario. After analyzing the variance and the shock lens scenarios, a comparison between both of them is performed.

Variance Lens

ANOVA results are presented in Table 4, where the degree of freedom (DOF) of each factor, F-ratios, p-values, and partial R^2 are shown. When all factors are considered together, the model is statistically significant with a 95% confidence level. The value of R^2 is 0.891, indicating that 89.1% of the variation in $PeakO_1$ can be explained by the structural factors. Furthermore, it can be seen that all structural factors are statistically significant, as well as the interaction between echelons and nodes. Figure 2 shows the main effects of structural factors (*E*, *N*, *DivF*) by plotting the mean $PeakO_1$ values for each level of the factor (Low, Medium, High). These values are calculated for a given structural factor by averaging the results obtained for all levels of the other structural factors (i.e. $PeakO_1$ for Low *DivF* is calculated by averaging the results obtained for Low, Medium and High levels of *E* and *N* when *DivF* was Low). In the subsequent analysis, all $PeakO_1$ values are divided by 10^4 (1E4).

Table 4. ANOVA results in Variance Lens scenario.

Factors	**DOF**	***F*-ratio**	***p*-value**	**R^2 (percent)**
Model	*17*	*1290.495*	*<0.001*	*89.1*
Echelons	2	10776.161	<0.001	88.9
Nodes	2	111.484	<0.001	7.7
Divergence	1	141.558	<0.001	5.0
Echelons * Nodes	4	3.196	0.013	0.5
Echelons * Divergence	2	1.498	0.224	0.1
Nodes * Divergence	2	2.130	0.119	0.2

Looking at the main effects in Figure 2 and in Table 4, it can be noted that the most significant factor is the number of echelons: SCNs with higher number of echelons show higher BWE, following an exponential trend. This result is in line with numerous works that already have identified the number of echelons as one of the most influential in contributing to the BWE (Bottani and Montanari, 2010; Paik and Bagchi, 2007; Chatfield et al., 2004; Disney et al., 2004, among others). In fact, by adding echelons to a SCN, the number of decision points increase, contributing to a higher distortion of the demand. Thus, each SCN member faces a more fluctuating order pattern (Paik and Bagchi, 2007). This behavior can be observed in Figure 2: SCNs with a low number of echelons show low values of $PeakO_1$, but this indicator abruptly increases when moving to SCNs with medium and high number of echelons.

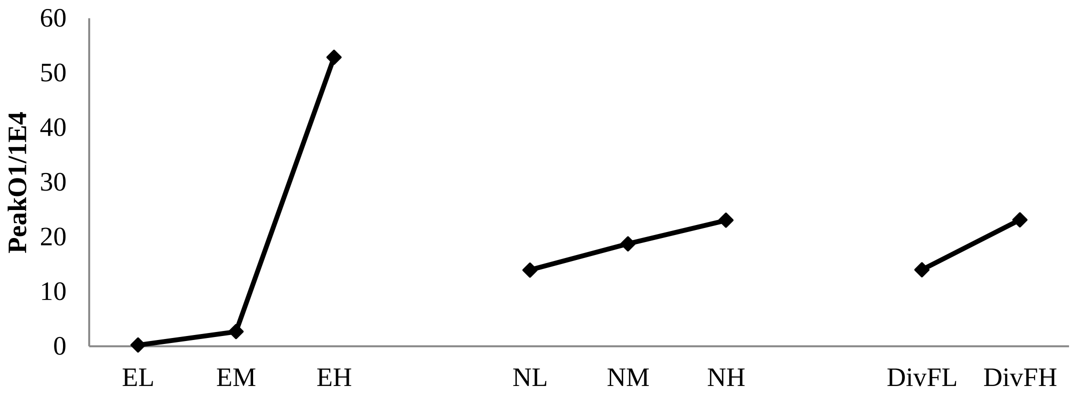

Figure 2. Main effects in Variance Lens scenario.

The number of nodes and the divergence of the SCN are both significant, but with a lower impact on the BWE as compared to the number of echelons. Considering that each node distorts the demand signal due to inventory policies, forecast rules and lack of coordination, demand distortion is higher when increasing the number of nodes in the SCN and hence, BWE increases. More specifically, by increasing the total number of nodes in a given SCN, we are in fact increasing the number of nodes per echelon (see Figure 3a). In this situation, nodes may have to fill the demand of a higher number of nodes and hence, they have to face a higher variability of orders and, consequently, BWE increases. However, under a stationary market demand nodes are able to make proper forecasts and fill the incoming orders with a high customer service, showing the SCN a stable behavior. Thus, an increase in the number of nodes per echelon has a low impact on the BWE.

The impact of the divergence of the SCN on the BWE is of similar magnitude as the impact of the number nodes. In a SCN with low divergence (see e.g. Figure 3b), nodes are uniformly distributed along the echelons (the number of nodes per echelon ($\sum_j n_{ij}$) is close to the average (*N/E)*). In this situation, demand is also uniformly distributed among the different nodes, thus limiting the amplification effect. However, when the divergence of the SCN increases ($\sum_j n_{ij}$ is far from *N/E*), there are one or more critical echelons in which the number of nodes abruptly increases and therefore, there are few nodes supplying a high number of nodes downstream in these echelons, as it can be seen in Figure 3b. This situation increases the variability of orders received by these nodes and hence, increases the BWE. But as for the number of nodes, the SCN shows a stable behavior due to a stationary market demand and thus, changing the divergence of the SCN has a low impact on the BWE.

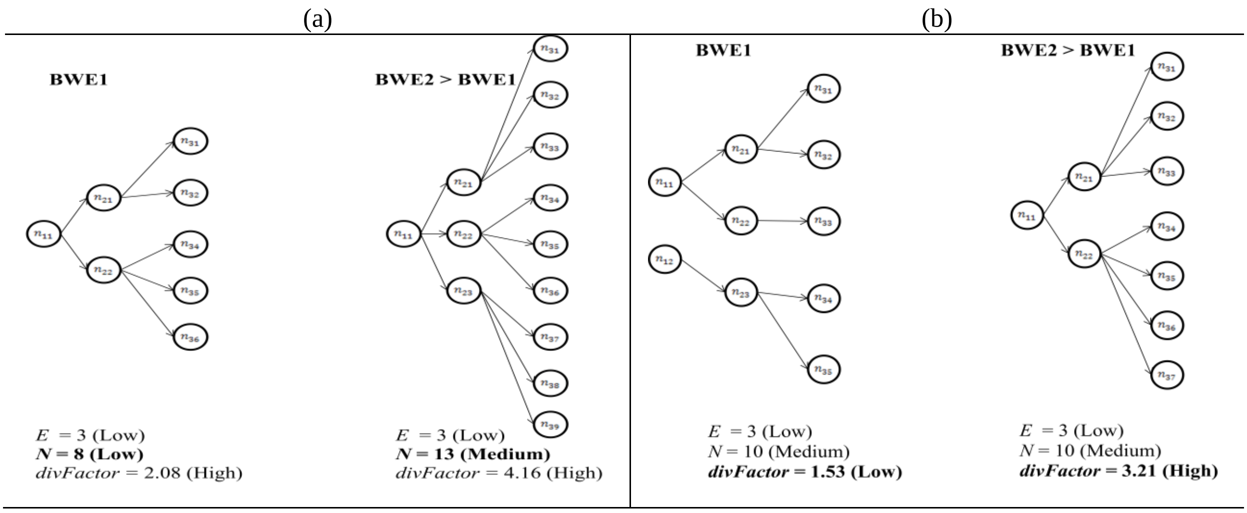

Figure 3. Increasing *N* (a) and *divF* (b) in a divergent SCN.

Finally, there is one significant interaction between the number of echelons and the number of nodes, although it has a low impact on the overall BWE and so it is not described.

Shock Lens

ANOVA results are summarized in Table 5. When all factors are considered together, the model is statistically significant at a 95% confidence level with an overall R^2 of 0.892, indicating that 89.2% of the variation in $PeakO_1$ can be explained by the structural factors considered. Furthermore, all factors are found to be statistically significant, as well as two of the interactions. Similarly to the variance lens analysis, Figure 4 shows the main effects of the structural factors by plotting the average $PeakO_1$ for each level of the factors (Low, Medium, High). Note that all values appear divided by 10^4 (1E4).

Table 5. ANOVA results in Shock Lens scenario.

Factors	**DOF**	***F*-ratio**	***p*-value**	**R^2 (percent)**
Model	*17*	*1305.427*	*<0.001*	*89.2*
Echelons	2	10231.880	<0.001	88.4
Nodes	2	439.303	<0.001	24.7
Divergence	1	693.143	<0.001	20.5
Echelons * Nodes	4	1.877	0.112	0.3
Echelons * Divergence	2	65.821	<0.001	4.7
Nodes * Divergence	2	7.909	<0.001	0.6

In view of the main effects in Figure 4 and the data from Table 5, it is noticeable that the most significant factor on the BWE is the number of echelons. In addition, the number of nodes and the divergence of the SCN have also a significant impact on the BWE.

SCNs with higher number of echelons show higher BWE, following an exponential trend. The shock in the average demand causes an unexpected multi stock-out at the retailer level. Nodes at this level react by placing orders larger than usual to the upstream nodes, which fall in a stock-out situation too. This effect is amplified from one echelon to another, increasing the fluctuation of orders through the SCN and causing the high $PeakO_1$ values observed in Figure 4.

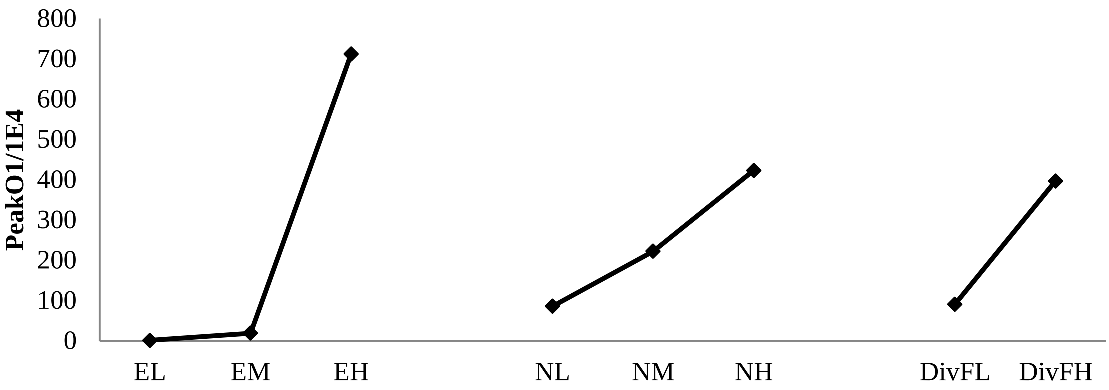

Figure 4. Main effects in Shock Lens scenario.

The number of nodes and the divergence of the SCN show now a significant and relative high impact on the BWE, as it can be deducted from partial R^2 in Table 5. In this case, the shock in the market demand makes a SCN with higher number of nodes to be more vulnerable to the BWE: the distortion of the demand signal caused by each node due to inventory policies, forecast rules and lack of coordination, becomes more important under a shock in demand than under a stationary demand. Furthermore, nodes filling demand from a higher number of nodes downstream are now affected by the unexpected shock wave transmitted upstream by the shock in demand and thus have to face a higher variability, consequently increasing the BWE.

In case of the divergence of SCNs in the shock lens scenario, the presence of critical echelons due to a high divergence leads to a situation in which there are few nodes supplying a high number of nodes downstream in these echelons and thus, they are very sensitive to the shock wave transmitted upstream by the shock in demand, showing a higher BWE.

There are two significant interactions in this scenario. The most important one takes place between the number of echelons and the divergence of the SCN. An “interaction plot” is used to determine the severity of this interaction. Due to the exponential nature of the obtained interaction curves, we have used logarithms to transform them into linear curves in order to make their interpretation clearer. In Figure 5a it can be seen that the linearized interaction curves are not parallel, which means that an interaction occurs between both factors. The *DivFH* curve shows a higher slope than the *DivFL* curve. Therefore BWE is more sensitive to the number of echelons in SCNs with high divergence than in SCNs with low divergence. In addition, BWE is more sensitive to the divergence in SCNs with high number of echelons than in SCNs with low number of echelons

It is important to notice that although Figure 5a may indicate that there is not a strong interaction between the number of echelons and the divergence of the SCN, it is necessary to consider that the interaction has been plotted over Ln($PeakO_1$). In order to clarify how important this interaction is, the original $PeakO_1$values are shown in Figure 5b, where it can be appreciated that both curves are different. Figure 5c plots the percentage increase of $PeakO_1$between the scenarios *DivFl* and *DivFH*. In this figure it can be seen a clear increasing trend as the number of echelons increase, thus confirming a strong interaction between these two structural factors. In addition, using a single variable test we have verified the significance of the interaction for each level of the structural factors: the impact of the different levels of the divergence of the SCN on the BWE have been tested for each level of the number of echelons and vice-versa, obtaining that all contrasts are statistically significant (p<0.001).

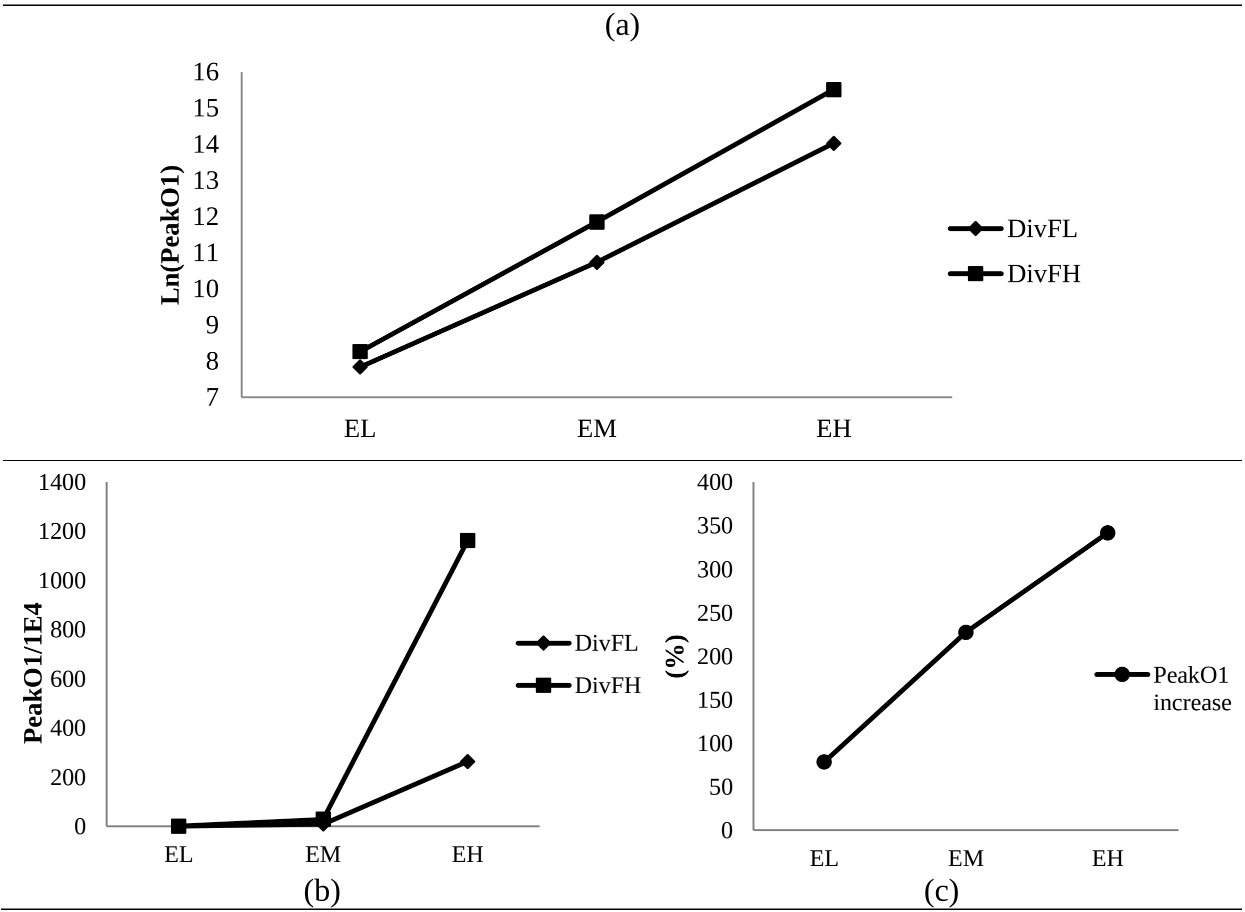

Figure 5. Interaction between *E* and the *DivF* in Shock Lens scenario.

Another significant interaction occurs between the number of nodes and the divergence of the SCN, but it has a very low impact on the overall BWE and so it is not described.

A comparison between the variance lens scenario and the shock lens scenario

In order to simplify the comparison between both scenarios, a summary of numeric results is provided in Table 6. This table shows the average of $PeakO_1$ (scaled by 10^4) and the 95% confidence intervals (CIs) given by their lower and upper bounds for all the 32 experimental points under analysis (18 for the variance lens and 18 for the shock lens).

There are three important differences between the variance and the shock lens scenarios. First of all, the number of nodes and the divergence of the SCN have a higher impact on the BWE in the shock lens scenario than in the variance lens scenario (see R^2 in Tables 4 and 5). This fact is confirmed by comparing the main effects of the number of nodes and the divergence of the SCN in both scenarios (see Figure 6): $PeakO_1$ curves show higher slopes in the shock lens scenario than in the variance lens scenario and hence, BWE is more sensitive to these factors in the former scenario than in the latter scenario. The higher number of nodes per echelon and/or the presence of critical echelons (SCNs with high divergence) make the SCN more vulnerable to an unexpected shock in demand and the consequent multi stock-out situation.

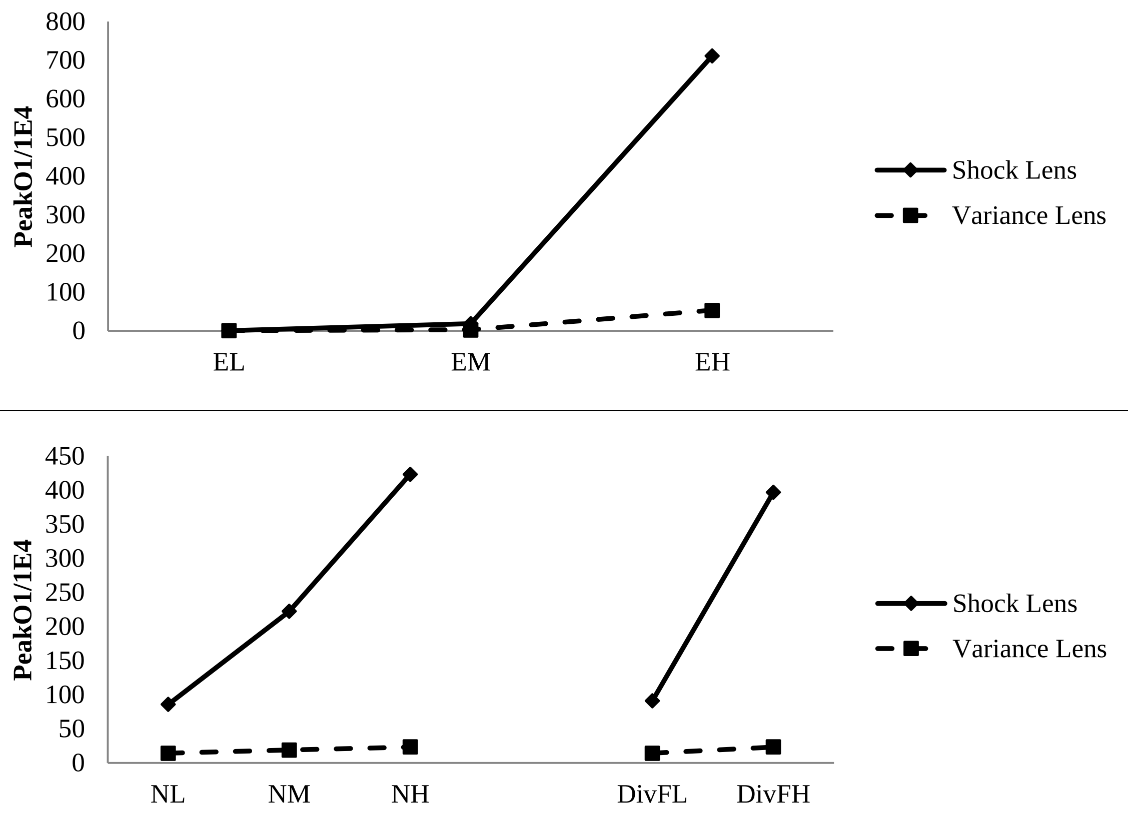

Figure 6. A comparison of the main effects of *E*, *N* and *DivF* between Variance Lens and Shock Lens scenarios.

Table 6. Average $PeakO_1$ and 95% confidence intervals from ANOVA.

Echelons	Nodes	Lens	Average $PeakO_1/1E4$	95% CI Lower Bound	95% CI Upper Bound
Divergence Factor: Low					
Low	Low	Variance	0.11682	0.10521	0.12843
		Shock	0.19005	0.16911	0.21099
	Medium	Variance	0.15991	0.14452	0.1753
		Shock	0.32386	0.27305	0.37467
	High	Variance	0.22061	0.19993	0.24129
		Shock	0.58536	0.52231	0.64841
Medium	Low	Variance	1.6834	1.50315	1.86365
		Shock	3.8115	3.10436	4.51864
	Medium	Variance	2.09657	1.947	2.24614
		Shock	8.14334	6.76431	9.52237
	High	Variance	2.51728	2.26373	2.77083
		Shock	13.89944	11.5298	16.26908
High	Low	Variance	31.47346	28.24269	34.70423
		Shock	116.54383	90.83327	142.25439
	Medium	Variance	39.51214	36.55075	42.47353
		Shock	240.26322	194.30447	286.22197
	High	Variance	48.0766	43.90626	52.24694
		Shock	431.59873	350.41371	512.78375
Divergence Factor: High					
Low	Low	Variance	0.14833	0.13362	0.16304
		Shock	0.24597	0.21766	0.27428
	Medium	Variance	0.23406	0.20556	0.26256
		Shock	0.65664	0.55743	0.75585
	High	Variance	0.30149	0.2749	0.32808
		Shock	1.05754	0.89348	1.2216
Medium	Low	Variance	2.26011	1.97476	2.54546
		Shock	10.84904	9.05746	12.64062
	Medium	Variance	3.45542	3.04776	3.86308
		Shock	25.46908	21.4585	29.47966
	High	Variance	3.84292	3.40116	4.28468
		Shock	48.33374	41.71319	54.95429
High	Low	Variance	47.77472	40.84654	54.7029
		Shock	381.67474	320.13077	443.21871
	Medium	Variance	66.88626	55.88368	77.88884
		Shock	1057.80539	885.78346	1229.82732
	High	Variance	83.14433	66.85235	99.43631
		Shock	2042.64747	1655.25052	2430.04442

A second important difference between both scenarios is that the BWE is higher in the shock lens scenario in all cases at a 95% confidence level (see Table 6 and Figure 6). Furthermore, since the shock lens scenario presents higher values of $PeakO_1$ and higher slopes than the variance lens scenario, the discrepancies in terms of BWE between both scenarios increase as the levels of the three structural factors increase. In order to quantify these discrepancies we employ a measure of the relative increase of the average BWE in the shock lens scenario over the average BWE in the variance lens scenario (see equation 7).

$$\Delta = \frac{(PeakO_1^{shockLens} - PeakO_1^{varianceLens})}{PeakO_1^{varianceLens}} * 100 \tag{7}$$

By plotting Δ for each level of the structural factors in Figure 7 we observe how the discrepancies between both scenarios show an increasing trend for each factor. This metric reveals an interesting behavior of the divergent SCN: as the structural complexity of the SCN increases (by means of the number of echelons, the number of nodes and/or its divergence) the differences between both scenarios increase and thus, the SCN becomes more vulnerable to unexpected shocks in market demand.

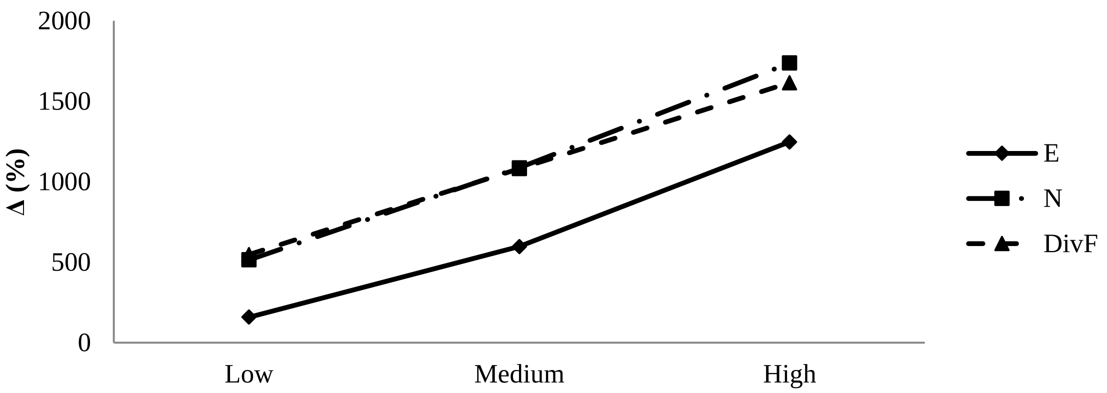

Figure 7. BWE discrepancies between Variance Lens and Shock Lens scenarios.

Finally, the third important difference between both scenarios refers to the interactions between the structural factors: in the variance lens scenario there is a significant interaction between the number of echelons and the number of nodes that however has a low impact on the overall BWE. In the shock lens scenario one of the two significant interactions found has an important impact on the overall BWE: the interaction between the divergence of the SCN and the number of echelons.

8 Implications of the research

There are some managerial implications that can be derived from this work that are related to the design of the SCN layout. The effect of the number of echelons on the BWE has been widely analyzed in literature, mostly in serial SCNs. However, this study suggests that a strategy based on the elimination of intermediate-channels, also known in BWE literature as Dell-Model strategies, is particularly effective for SCNs operating in a stable market environment. Considering that the global crisis is generating impetuous changes in the market demand in several sectors (Cannella et al., 2014a), the advocated elimination of intermediate-channels can also be associated to a "structural lean strategy" (Christopher and Holweg, 2011; Holweg, 2007), aimed at reducing the SCN complexity. This is mainly because the impact of the number of nodes and of the divergence of the SCN imposes new challenges in the SCN design effort.

The number of nodes is related to the average number of nodes (or entities) within each echelon. Since the analysis focuses on divergent SCNs, the total number of nodes is directly related to the number of retailers (e.g. a high value of N also means a high number of retailers). The present study shows that in case of SCNs facing a stable demand, the total number of entities in the SCN do not affect the BWE. However, in case of SCNs facing an unstable demand with violent changes in the demand mean, the total number of entities in the SCN has a direct impact on the BWE. Therefore, managers and designers should pay special attention in optimizing the geographical distribution of entities in each echelon to avoid unnecessary stock points and retailers, thus limiting the vulnerability of the SCN to unforeseen shocks in demand. This strategy is in line with the risk pooling effect, which states that a reduction of the number of retailers reduces the risk faced by them due to the market demand variability, thus reducing safety stocks and derived costs (Miranda and Garrido, 2009).

The divergence of the SCN describes the distribution of nodes along the echelons. The present study shows that, as for the number of nodes, this factor acquires strategic relevance in terms of dynamic performance under volatile market conditions. Hence, managers and designers should try to design the SCN layout through a smooth increase of the number of entities downstream to avoid the presence of critical echelons in which there are few entities dealing with the supply of a high number of other entities in the subsequent echelon, thus limiting the vulnerability of the SCN.

However, it is not always possible to reduce the complexity of SCN layouts. Depending on the typology of products, on the technological process for generating such products, on the challenges imposed by competitors, on the specific manufacturing or distribution sector, on the geographical dispersion and so on, there are technological, strategic and humanitarian limitations that impede a modification of the SCN layout. In these cases, this study suggests that a SCN characterized by a high level of structural complexity is particularly exposed to the detrimental effect caused by a volatile market environment. For this reason, in order to increase the resilience of such SCNs, it the adoption of the BWE avoidance techniques, like information sharing and smoothing replenishment rules could be a vital strategy.

9 Conclusions and future research

The structural design of the SCN, defined by the number of echelons, the number of nodes and the divergence of the SCN, has been analyzed in terms of BWE. A collection of divergent SCNs with random structures according to different levels of their structural factors have been modeled and simulated, and output data has been statistically analyzed. Two independent scenarios with different demand patterns have been considered: the former is characterized by a stationary and normally distributed demand input, while the latter is characterized by a normally distributed demand input which suffers, at a given time, a violent increment in its mean. It has been shown that in case of a stationary demand, the number of echelons is the dominant structural factor influencing the BWE, which is in line with most of scientific works on BWE. However, in case of an unforeseen shock in demand, the rest of the structural factors considered gain influence on BWE: increasing the number of nodes and the divergence of the SCN will increase BWE. Furthermore, BWE is always higher in the case of an impulse in the end-customer demand. Additionally, BWE is more sensitive to the structural design of the SCN in this scenario than in the scenario with stationary demand. Hence, as SCNs size increases in terms of number of echelons or number of nodes, or increases its divergence, they also become more vulnerable to unexpected violent changes in demand mean. In other words, as SCNs become more complex, they fall in a more vulnerable situation under uncertainties in market demand.

The current work presents a good opportunity for future research. Since there are multiple possible configurations of SCNs, we have limited the present analysis to one of them, i.e. the divergent/distribution SCN. A very interesting research opportunity arises from the extension of this work to a convergent/assembly SCN, determining a "convergence factor" and analyzing how the convergence of a SCN may impact on the BWE as well as the interaction of this structural factor with the number of echelons and the number of nodes. This study would lead to a comparison between the divergent and the convergent SCNs in order to benchmark the sensitivity of their dynamic behaviors to their structural design and to uncertainties in market demand. A step further in this line is to model a conjoined SCN (a mixed divergent/convergent SCN) and try to unify the divergence factor and the convergence factor into one single structural factor that perfectly identify this kind of networks. Analyzing how the structural design of these complex configurations (by using different combinations of divergence and convergence) impact on the SCN dynamics could be very interesting.

A further limitation of this study is the assumption of homogeneous degree distributions: all nodes in the same echelon have similar connection degrees (or similar number of links). This assumption has been made to simplify the design of experiments and the conclusions of the paper. However, an interesting research could be to analyze the impact that the connection degree may have on the BWE, determining the role of "poor connected" nodes as well as "high connected" nodes (usually causing bottlenecks). In addition, this study can be performed over divergent, convergent or conjoined SCNs. Also, a natural extension of this work could be to include operational factors such as stochastic lead times, demand variability, forecast policy, inventory policy, etc. into the statistical analysis and determine the interaction between operational and structural factors on the BWE.

Finally, the findings of this study suggest further multidisciplinary research in the field of SCN management and complex systems. The SCNs are, in fact, complex systems, since their overall behavior cannot be described exhaustively, although there is comprehensive knowledge of its components and their interaction (Pratt et al. 2005). Hence, the analysis of SCNs should turn on considering complex SCNs in further studies, in order to get closer to the dynamics of real SCNs. The present work is a step through modeling SCNs as complex systems. According to Reiß (1993), four dimensions of complexity exist: multiplicity (which leads to the variety of a system), variance (resulting in the heterogeneity of the system), changeability (determining the variability of the system), and ambiguity (leading to uncertainty). In the current work, one of these drivers of complexity is addressed, i.e. multiplicity. As compared with the traditional serial SCN, the divergent SCNs analyzed here have a higher number of elements and interdependence. In order to better understand complex SCNs, future research should consider exploring all the dimensions of complexity identified by Reiß (1993). In other words, future research should focus on modeling SCNs with high number of elements and interdependence (multiplicity), including diversity of elements, i.e., elements are different between them (variance, heterogeneity), and the ability of elements to change their status over time (changeability, chaos), as well as ambiguity and uncertainty.

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References

Agrawal, S., Sengupta, R.N., Shanker, K. 2009. Impact of Information Sharing and Lead Time on Bullwhip Effect and On-hand Inventory. *European Journal of Operational Research*, 192 (2), 576–593.

Akkermans, H., Voss, C. 2013. The service bullwhip effect. *International Journal of Operations and Production Management*, 33 (6), 765-788.

Bailey, K., Francis, M. 2008. Managing Information Flows for Improved Value Chain Performance. *International Journal of Production Economics*, 111 (1), 2–12.

Balan, S., Vratb, P., Kumarc, P. 2009. Information Distortion in a Supply Chain and Its Mitigation Using Soft Computing Approach. *The International Journal of Management Science*, 37 (2), 282–299.

Barabási, A.L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., Vicsek, T. 2002. Evolution of the social network of scientific collaborations. *Physica A: Statistical Mechanics and its Applications*, 311 (3-4), 590-614.

Bayraktar, E., Koh, L. S. C., Gunasekaran, A., Sari, K., Tatoglu, E. 2008. The Role of Forecasting on Bullwhip Effect for E-SCM Applications. *International Journal of Production Economics*, 113 (1), 193–204.

Beamon, B.M., Chen, V.C.P. 2001. Performance analysis of conjoined supply chains. *International Journal of Production Research*, 39 (14), 3195-3218.

Ben-Tal, A., Golany, B., Shtern, S. 2009. Robust Multi-Echelon Multi-Period Inventory Control. *European Journal of Operational Research*, 199 (3), 922–935.

Bhattacharya, R., Bandyopadhyay, S., 2011. A review of the causes of bullwhip effect in a supply chain. *International Journal of Advanced Manufacturing Technology*, 54 (9-12), 1245-1261.

Bottani, E., Montanari, R. 2010. Supply chain design and cost analysis through simulation. *International Journal of Production Research*, 48 (10), 2859-2886.

Bray, R.L., Mendelson, H. 2012. Information transmission and the bullwhip effect: An empirical investigation. *Management Science*, 58 (5), 860-875.

Bruccoleri, M., Cannella, S., La Porta, G. 2014. Inventory record inaccuracy in supply chains: The role of workers' behavior. *International Journal of Physical Distribution and Logistics Management*, 44 (10), 796-819.

Cachon, G. P., Fisher, M. 2000. Supply Chain Inventory Management and the Value of Shared Information. *Management Science*, 46 (8), 1032–1048.

Cachon, G. P., Lariviere, M. A. 2001. Contracting to Assure Supply: How to Share Demand Forecasts in a Supply Chain. *Management Science*, 47 (5), 629–646.

Cachon, G. P., Randall, T., Schmidt, G. M. 2007. In Search of the Bullwhip Effect. *Manufacturing & Service Operations Management*, 9 (4), 457–479.

Campuzano, F., Guillamon, A., Ros, L. 2009. The Influence of Lead Time Variability on Supply Chain Costs: Analysis of Its Impact on the Bullwhip Effect. *The IUP Journal of Supply Chain Management*, 6 (3), 15-26.

Cannella, S., Barbosa-Póvoa, A.P., Framinan, J.M., Relvas, S. 2013. Metrics for bullwhip effect analysis. *Journal of the Operational Research Society*, 64 (1), 1-16.

Cannella, S., Ashayeri, J., Miranda, P.A., Bruccoleri, M. 2014a. Current economic downturn and supply chain: the significance of demand and inventory smoothing. *International Journal of Computer Integrated Manufacturing*, 27 (3), 201-212.

Cannella, S., Framinan, J.M., Barbosa-Povoa, A.P. 2014b. An IT-enabled supply chain model: A simulation study. *International Journal of Systems Science*, 45 (11), 2327-2341.

Cannella S., Framinan J.M., Bruccoleri, M., Barbosa-Povoa A.P., Relvas S. 2014c. The effect of Inventory Record Inaccuracy in Information Exchange Supply Chains. *European Journal of Operational Research*. doi:10.1016/j.ejor.2014.11.021.

Cannella S. 2014. Order-up-to policies in information exchange supply chains. *Applied Mathematical Modelling*, 38 (23), 5553-5561.

Chan, F. T. S., Chung, S. H., Wadhwa, S. 2004. A Heuristic Methodology for Order Distribution in a Demand Driven Collaborative Supply Chain. *International Journal of Production Research*, 42 (1), 1–19.

Chan, F.T.S, Prakash, A. 2012. Inventory management in a lateral collaborative manufacturing supply chain: a simulation study. *International Journal of Production Research*, 50 (16), 4670-4685.

Chatfield, D. C., Kim, J. G., Harriso, T. P. 2004. The Bullwhip Effect—Impact of Stochastic Lead Time, Information Quality, and Information Sharing: a Simulation Study. *Production and Operations Management*, 13 (4), 340–353.

Chatfield, D.C., Hayya, J.C., Cook, D.P. 2012. Stockout propagation and amplification in supply chain inventory systems. *International Journal of Production Research*, 51 (5), 1491-1507.

Chatfield, D.C., Pritchard, A.M. 2013. Returns and the bullwhip effect. *Transportation Research Part E: Logistics and Transportation Review*, 49 (1), 159-175.

Chen, F., Drezner, Z., Ryan, J.K., Simchi-Levi, D. 2000. Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. *Management Science*, 46 (3), 436–443.

Chen, H., Chen, J., Chen, Y. 2006. A Coordination Mechanism for a Supply Chain with Demand Information Updating. *International Journal of Production Economics*, 103 (1), 347–361.

Chen, L., Lee, H. L. 2009. Information Sharing and Order Variability Control under a Generalised Demand Model. *Management Science*, 55 (5), 781–797.

Chen, H.-H. 2012. Simulating analysis of complex supply chain networks invulnerability. *Lecture Notes in Electrical Engineering*, 154, 1229-1235.

Cheng, L.C. 2009. Impact of Inventory Policy Consistency on the Three Stage Supply Chain Performance. *Journal of Academy of Business and Economics*, 9 (4), 33–53.

Childerhouse, P., Disney, S. M., Towill, D. R. 2008. On the Impact of Order Volatility in the European Automotive Sector. *International Journal of Production Economics*, 114 (1), 2–13.

Choi, T.Y., Dooley, K.J.,Rungtusanatham, M. 2001. Supply networks and complex adaptive systems: Control versus emergence. *Journal of Operations Management*, 19 (3), 351-366.

Christopher, M., Holweg, M. 2011. "Supply Chain 2.0": Managing supply chains in the era of turbulence. *International Journal of Physical Distribution and Logistics Management*, 41 (1), 63-82.

Ciancimino E., Cannella S., Bruccoleri M., Framinan, J.M. 2012. On the bullwhip avoidance phase: the Synchronised Supply. *European Journal of Operational Research*, 22 (1), 49–63.

Corominas, A. 2013. Supply chains: what they are and the new problems they raise. *International Journal of Production Research*, 51 (23-24), 6828-6835.

Crespo Márquez, A. 2010. Dynamic Modelling for Supply Chain Management: Dealing with Front-end, Back-end and Integration Issues. London: Springer.

Croson, R., Donohue, K. 2005. Upstream versus Downstream Information and Its Impact on the Bullwhip Effect. *System Dynamics Review*, 21 (3), 249–260.

Croson, R., Donohue, K. 2006. Behavioral causes of the bullwhip effect and the observed value of inventory information. *Management Science*, 52 (3), 323-336.

Dejonckheere, J., Disney, S. M., Lambrecht, M. R., Towill, D. R. 2002. Transfer Function Analysis of Forecasting Induced Bullwhip in Supply Chains. *International Journal of Production Economics*, 78 (2), 133–144.

Dejonckheere, J., Disney, S. M., Lambrecht, M. R., Towill, D. R. 2003. Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research*, 147 (3), 567-590.

Dejonckheere, J., Disney, S. M., Lambrecht, M. R., Towill, D. R. 2004. The impact of information enrichment on the Bullwhip effect in supply chains: A control engineering perspective. *European Journal of Operational Research*, 153 (3), 727-750.

Disney, S. M., Towill, D. R. 2003. On the Bullwhip and Inventory Variance Produced by an Ordering Policy. *The International Journal of Management Science*, 31 (3), 157–167.

Disney, S.M., Naim, M.M., Potter, A., 2004. Assessing the impact of e-business on supply chain dynamics. *International Journal of Production Economics*, 89 (2), 109-118.

Disney, S.M., Lambrecht, M., 2008. On Replenishment Rules, Forecasting, and the Bullwhip Effect in Supply Chains. *Foundations and Trends in Technology, Information and Operations Management*, 2 (1), 1-80.

Dominguez, R., Framinan, J.M. 2013. A decisión management tool: modelling the order fulfilment process by multi-agent systems. *International Journal of Management and Decision Making*, 12 (3), 240-258.

Dominguez, R., Cannella, S., Framinan, J.M. 2014. On bullwhip-limiting strategies in divergent supply chain networks. *Computers and Industrial Engineering*, 73 (1), 85-95.

Dominguez, R., Cannella, S., Framinan, J.M. 2015. On returns and network configuration in supply chain dynamics. *Transportation Research Part E: Logistics and Transportation Review*, 73, 152-167.

Dong, S.-H., Xi, B., Tian, L.-N., Huang, Q.-G., Chen, H.-X. 2006. An agent-based architecture for supply chain management. *Proceedings of the 2006 International Conference on Machine Learning and Cybernetics*, art. no. 4028046, 137-141.

Ganesh, M., Raghunathan, S., and Rajendran, C. 2008. The Value of Information Sharing in a Multi-Product Supply Chain with Product Substitution. *IIE Transactions (Institute of Industrial Engineers)*, 40 (12), 1124-1140

Geary, S., Disney, S. M., and Towill, D. R. 2006. On Bullwhip in Supply Chains—Historical Review, Present Practice and Expected Future Impact. *International Journal of Production Economics*, 101 (1 SPEC. ISS.), 2-18.

Gerschberger, M., Engelhardt-Nowitzki, C., Kummer, S., Staberhofer, F. 2012. A model to determine complexity in supply networks. *Journal of Manufacturing Technology Management*, 23 (8), 1015-1037.

Giard, V., Sali, M. 2013. The bullwhip effect in supply chains: A study of contingent and incomplete literature. *International Journal of Production Research*, 51 (13), 3880-3893.

Gonçalves, P., Hines, J., and Sterman, J., 2005. The impact of endogenous demand on push-pull production system. *System Dynamics Review*, 21 (3), 187-216.

Govindu, R., Chinnam, R.B. 2010. A software agent-component based framework for multi-agent supply chain modeling and simulation. *International Journal of Modeling and Simulation*, 30 (2), 155-171.

Hassanzadeh, A., Jafarian, A., Amiri, M. 2014. Modeling and analysis of the causes of bullwhip effect in centralized and decentralized supply chain using response surface method. *Applied Mathematical Modeling*, 38 (9-10), 2353–2365.

Hearnshaw, E.J.S., Wilson, M.M.J. 2013. A complex network approach to supply chain network theory. *International Journal of Operations and Production Management*, 33 (4), 442-469.

Hinkelmann, K., Kempthorne, O. 1994. Design and Analysis of Experiments: Volume I – Introduction to Experimental Design, Wiley, New York, NY.

Holweg, M. 2007. The genealogy of lean production. *Journal of Operations Management*, 25 (2), 420-437.

Holweg, M., Disney, S.M., Holmström, J., Småros, J. 2005. Supply chain collaboration: making sense of the strategy continuum. *European Management Journal*, 23 (2), 170-181.

Holweg, M., Bicheno, J. 2002. Supply chain simulation - A tool for education, enhancement and endeavour. *International Journal of Production Economics*, 78 (2), 163-175

Huang, G. Q., Lau, J. S. K., Mak, K. L., and Liang, L. 2005. Distributed Supply-Chain Project Rescheduling: Part I—Impacts of Information-Sharing Strategies. *International Journal of Production Research*, 43 (24): 5107–5129.

Hung, S.-J. 2011. Activity-based divergent supply chain planning for competitive advantage in the risky global environment: A DEMATEL-ANP fuzzy goal programming approach. *Expert Systems with Applications*, 38 (8), 9053-9062.

Hussain, M., Drake, P.R., Lee, D.M. 2012. Quantifying the impact of a supply chain's design parameters on the bullwhip effect using simulation and Taguchi design of experiments. *International Journal of Physical Distribution and Logistics Management*, 42 (10), 947-968.

Hwarng, H.B., Chong, C.S.P., Xie, N., Burgess, T.F. 2005. Modelling a complex supply chain: Understanding the effect of simplified assumptions. *International Journal of Production Research*, 43 (13), 2829-2872.

Julka, N., Srinivasan, R., Karimi, I. 2002. Agent-based supply chain management - 1: Framework. *Computers and Chemical Engineering*, 26 (12), 1755-1769.

Jung, H., Chen, F. F., Jeong, B. 2007. Decentralised Supply Chain Planning Framework for Third Party Logistics Partnership. *Computers & Industrial Engineering*, 55 (2), 348–364.

Kelepouris, T., Miliotis, P., Pramatari, K. 2007. The Impact of Replenishment Parameters and Information Sharing on the Bullwhip Effect: a Computational Study. *Computers & Operations Research*, 35 (11), 3657–3670.

Khumwan, N., Pichitlamken, J. 2007. The sensitivity analysis of the bullwhip effect in a three-level supply chain with stochastic demands and lead times. *Proceedings of The 2nd International Conference on Operations and Supply Chain Management, Bangkok, May 18-20, 2007.*

Kim, Y., Choi, T.Y., Yan, T., Dooley, K. 2011. Structural investigation of supply networks: A social network analysis approach. *Journal of Operations Management*, 29 (3), 194-211.

Lau, J. S. K., Huang, G. Q., Mak, K. L., Liang, L. 2005. Distributed Project Scheduling with Information Sharing in Supply Chains: Part II—Theoretical Analysis and Computational Study. *International Journal of Production Research*, 43 (23), 4899–4927.

Lau, J. S. K., Huang, G. Q., Mak, K. L. 2004. Impact of Information Sharing on Inventory Replenishment in Divergent Supply Chains. *International Journal of Production Research*, 42 (5), 919–941.

Lee, H. L., Padmanabhan, V., Seungjin, W. 1997. Information Distortion in a Supply Chain: the Bullwhip Effect. *Management Science*, 43 (4), 546–558.

Lee, L. H., Padmanabhan, V., Whang, S. 2004a. Information Distortion in a Supply Chain: the Bullwhip Effect. *Management Science*, 50 (12), 1875–1886.

Lee, H. L., Padmanabhan, V., Whang, S. 2004b. Comments on “Information Distortion in a Supply Chain: the Bullwhip Effect”. *Management Science*, 50 (12), 1887–1893.

Li, L., Zhang, H. 2008. Confidentiality and Information Sharing in Supply Chain Coordination. *Management Science*, 54 (8), 1467–1481.

Li, Z., Gao, L. 2008. The Effects of Sharing Upsteam Information on Product Rollover. *Production and Operations Management*, 17 (5), 522–531.

Li, G., Ji, P., Sun, L.Y., Lee, W.B. 2009. Modeling and simulation of supply network evolution based on complex adaptive system and fitness landscape. *Computers and Industrial Engineering*, 56 (3), 839-853.

Li, G., Xuan, Q., Song, Z., Jin, X. 2010a. Complex supply networks evolving model: Complex networks perspective. *Proceedings of 2010 IEEE International Conference on Intelligent Systems and Knowledge Engineering, ISKE 2010*, art. no. 5680780, 511-516.

Li, G., Yang, H., Sun, L., Ji, P., Feng, L. 2010b. The evolutionary complexity of complex adaptive supply networks: A simulation and case study. *International Journal of Production Economics*, 124 (2), 310-330.

Li, C. 2013. Controlling the bullwhip effect in a supply chain system with constrained information flows. *Applied Mathematical Modelling*, 37 (4), 1897-1909.

Li, C., Liu, S. 2013. A robust optimization approach to reduce the bullwhip effect of supply chains with vendor order placement lead time delays in an uncertain environment. *Applied Mathematical Modelling*, 37 (3), 707-718.

Lin, W.-J., Jiang, Z.-B., Wang, L. 2014a. Modelling and analysis of the bullwhip effect with customers' baulking behaviours and production capacity constraint. *International Journal of Production Research*, 52 (16), 4835-4852.

Lin, W.-J., Jiang, Z.-B., Liu, R., Wang, L. 2014b. The bullwhip effect in hybrid supply chain. *International Journal of Production Research*, 52 (7), 2062-2084.

Liu, M., Vepkhvadze, N., Srinivasan, M. M. 2009. What is the Value of Real-Time Shipment Tracking Information? *IIE Transactions (Institute of Industrial Engineers)*, 41 (12), 1019-1034.

Long, Q., Lin, J., Sun, Z., 2011. Modeling and distributed simulation of supply chain with a multi-agent platform. *International Journal of Advanced Manufacturing Technology*, 55 (9-12), 1241-1252.

Lu, J., Humphreys, P., McIvor, R., Maguire, L., Wiengarten, F. 2012. Applying genetic algorithms to dampen the impact of price fluctuations in a supply chain. *International Journal of Production Research*, 50 (19), pp. 5396-5414.

Ma, Y., Wang, N., Che, A., Huang, Y., Xu, J. 2013. The bullwhip effect under different information-sharing settings: A perspective on price-sensitive demand that incorporates price dynamics. *International Journal of Production Research*, 51 (10), 3085-3116.

Min, H., Zhou, G., 2002. Supply chain modeling: past, present and future. *Computers & Industrial Engineering*, 43 (1-2), 231-249.

Miragliotta, G. 2006. Layers and mechanisms: A new taxonomy for the Bullwhip Effect. *International Journal of Production Economics*, 104 (2), 365-381.

Miranda, P.A., Garrido, R.A. 2009. Inventory service-level optimization within distribution network design problem. *International Journal of Production Economics*, 122 (1), 276-285.

Mitchell, T. (1924). Competitive illusion as a cause of business cycles. *Quarterly Journal of Economics*, 38, 631-652.

Moinzadeh, K. 2002. A Multi-Echelon Inventory System with Information Exchange. *Management Science*, 48 (3), 414–426.

Nepal, B., Murat, A., Babu Chinnam, R. 2012. The bullwhip effect in capacitated supply chains with consideration for product life-cycle aspects. *International Journal of Production Economics*, 136 (2) 318–331.

Nienhaus, J., Ziegenbein A., Schoensleben, P. 2006. How Human Behaviour Amplifies the Bullwhip Effect a Study Based on the Beer Distribution Game Online. *Production Planning & Control*, 17 (6), 547–557.

O'Donnell, T., Humphreys, P., McIvor, R., Maguire, L. 2009. Reducing the Negative Effects of Sales Promotions in Supply Chains Using Genetic Algorithms. *Expert Systems with Applications*, 36 (4), 7827–7837.

Ouyang, Y. 2007. The Effect of Information Sharing on Supply Chain Stability and the Bullwhip Effect. *European Journal of Operational Research*, 182 (3), 1107–1121.

Ouyang, Y., Li, X. 2010. The Bullwhip Effect in Supply Chain Networks. *European Journal of Operational Research*, 201 (3), 799–810.

Özelkan, E.C., Çakanyildirim, M., C. 2009. Reverse Bullwhip Effect in Pricing. *European Journal of Operational Research*, 192 (1), 302–312.

Paik, S.-K., Bagchi, P.K., 2007. Understanding the causes of the bullwhip effect in a supply chain. *International Journal of Retail and Distribution Management*, 35 (4), 308-324.

Patel, S. K., Jena, P. 2012. Effect of Forecasting on Bullwhip Effect in Supply Chain Management. In *6th ISDSI international Conference, IBS, Hyderabad, Dec 27-29, 2012*.

Pathak, S.D., Day, J.M., Nair, A., Sawaya, W.J., Kristal, M.M. 2007. Complexity and adaptivity in supply networks: Building supply network theory using a complex adaptive systems perspective. *Decision Sciences*, 38 (4), 547–580.

Pereira, J., Takahashi, K., Ahumada, L., Paredes, F. 2009. Flexibility Dimensions to Control the Bullwhip Effect in a Supply Chain. *International Journal of Production Research*, 47 (22), 6357–6374.

Potter, A., Disney, S.M. 2006. Bullwhip and batching: An exploration. *International Journal of Production Economics*, 104 (2), 408-418.

Pratt, J., Gordon, P., Plamping, D. 2005. Whole Systems: Putting Theory Into Practice in Organisations. Radcliffe Publishing.

Reiß, M. (1993), Komplexitätsmanagement I (Complexity Management I). in: WISU, pp. 132–137.

Ryu, S.-J., Tsukishima, T., Onari, H. 2009. A Study on Evaluation of Demand Information—Sharing Methods. *International Journal of Production Economics*, 120 (1), 182–189.

Shan, J., Yang, S., Yang, S., Zhang, J. 2013. An empirical study of the bullwhip effect in china. *Production and Operations Management*, 23 (4), 537-551.

Sodhi, M.S., Tang, C.S. 2011. The incremental bullwhip effect of operational deviations in an arborescent supply chain with requirements planning. *European Journal of Operational Research*, 215 (2), 374-382

Springer, M., Kim, I. 2010. Managing the Order Pipeline to Reduce Supply Chain Volatility. *European Journal of Operational Research*, 203 (2), 380–392.

Stadtler, H. 2005. Supply chain management and advanced planning - Basics, overview and challenges. *European Journal of Operational Research*, 163 (3), 575-588.

Sucky, E. 2009. The Bullwhip Effect in Supply Chains – An Overestimated Problem?. *International Journal of Production Economics*, 118 (1), 311–322.

Swaminathan, J.M., Smith, S.F., Sadeh, N.M. 1998. Modeling supply chain dynamics: a multi-agent approach. *Decision Sciences*, 29 (3), 607–631.

Syntetos, A.A., Boylan, J.E., Disney, S.M. 2009. Forecasting for inventory planning: a 50-year review. *Journal of the Operational Research Society*, 60 (5), 149-160,

Syntetos, A.A., Georgantzas, N.C., Boylan, J.E., Dangerfield, B.C. 2011. Judgement and supply chain dynamics. *Journal of the Operational Research Society*, 62 (6), 1138-1158.

Surana, A., Kumara, S., Greaves, M., Raghavan, U.N. 2005. Supply-chain networks: A complex adaptive systems perspective. *International Journal of Production Research*, 43 (20), 4235–4265.

Thonemann, U. W. 2002. Improving Supply-Chain Performance by Sharing Advance Demand Information. *European Journal of Operational Research*, 142 (1), 81–107.

Towill, D.R., Zhou, L., Disney, S.M., 2007. Reducing the bullwhip effect: Looking through the appropriate lens. *International Journal of Production Economics*, 108 (1-2), 444-453.

Trapero, J.R., Kourentzes, N., Fildes, R. 2012. Impact of information exchange on supplier forecasting performance. *Omega, the International Journal of Management Science*, 40 (6), 738–747.

Turrisi M., Bruccoleri M., Cannella S. 2013 Impact of reverse logistics on supply chain performance. *International Journal of Physical Distribution & Logistics Management*, 43 (7), 564 - 585.

Viswanathan, S., Widiarta, H., Piplani, R. 2007. Value of Information Exchange and Synchronization in a Multi-Tier Supply Chain. *International Journal of Production Research*, 45 (21), 5057–5074.

Von Massow, M., Canbolat, M. 2014. A strategic decision framework for a value added supply chain. *International Journal of Production Research*, 52 (7), 1940-1955.

Wang, J., Jia, J., Takahashi, K. 2005. A Study on the Impact of Uncertain Factors on Information Distortion in Supply Chains. *Production Planning & Control*, 16 (1), 2–11.

Wang, K., Zeng, Z., Sun, D. 2008. Structure analysis of supply chain networks based on complex network theory. *4th international conference on semantics, knowledge and grid*, 3–5 December, Beijing, China.

Wangphanich, P., Kara, S., Kayis, B. 2010. Analysis of the Bullwhip Effect in Multi-Product, Multi-Stage Supply Chain Systems– A Simulation Approach. *International Journal of Production Research*, 48 (15), 4501–4517.

Wikner, J., Naim, M. M., Towill, D.R., 1992. The system simplification approach in understanding the dynamic behaviour of a manufacturing supply chain. *Journal of Systems Engineering*, 2 (3), 164-178

Wen, L., Guo, M., Wng, L. 2012. The directed complex network application in the supply chain. *Proceedings - 2012 3rd International Conference on Digital Manufacturing and Automation, ICDMA 2012* , art. no. 6298664, 911-914.

Wong, W. K., Qi, J., Leung, S. Y. S. 2009. Coordinating Supply Chains with Sales Rebate Contracts and Vendor-Managed Inventory. *International Journal of Production Economics*, 120 (1), 151–161.

Wright, D., Yuan, X. 2008. Mitigating the Bullwhip Effect by Ordering Policies and Forecasting Methods. *International Journal of Production Economics*, 113 (2), 587–597.

Wu, Y. N., Cheng, E. T. C. 2008. The Impact of Information Sharing in a Multiple-Echelon. *International Journal of Production Economics*, 115 (1), 1–11.

Wu, D.Y., Katok, E. 2006. Learning, communication, and the bullwhip effect. *Journal of Operations Management*, 24 (6), 839-850.

Xuan, Q., Du, F., Li, Y., Wu, T.-J. 2011. A framework to model the topological structure of supply networks. *IEEE Transactions on Automation Science and Engineering*, 8 (2), 442-446.

Yang, T., Wen, Y.-F., Wang, F.-F. 2011. Evaluation of robustness of supply chain information-sharing strategies using a hybrid Taguchi and multiple criteria decision-making method. *International Journal of Production Economics*, 134 (2), 458-466.

Yee, S. T. 2005. Impact Analysis of Customised Demand Information Sharing on Supply Chain Performance. *International Journal of Production Research*, 43 (16), 3353–3373.

Zhang, X. 2004. The Impact of Forecasting Methods on the Bullwhip Effect. *International Journal of Production Economics*, 88 (1), 15–27.

Zhao, X., Xie, J. 2002. Forecasting Errors and the Value of Information Sharing in a Supply Chain. *International Journal of Production Research*, 40 (2), 311–335.

Zotteri, G. 2013. An empirical investigation on causes and effects of the Bullwhip-effect: Evidence from the personal care sector. *International Journal of Production Economics*, 143, pp. 489-498.