Serial versus divergent supply chain networks: a comparative analysis of the bullwhip effect

Roberto Dominguez[1], Jose M. Framinan[2], Salvatore Cannella[3]

[1] Industrial Management, School of Engineering, University of Seville, Ave. Descubrimientos s/n, Seville, E41092, Spain; tel: (+34) 954488137; e-mail: rdc@us.es (corresponding author)

[2] Industrial Management, School of Engineering, University of Seville, Ave. Descubrimientos s/n, Seville, E41092, Spain; tel: (+34) 954487214; e-mail: framinan@us.es

[3] tel: (+39) 3386263359; e-mail: salvatore.cannella@ist.utl.pt

The amplification of demand variation in a supply chain network (SCN) is a well-known phenomenon called the bullwhip effect, which creates inefficiencies due to high variation in the order quantities placed between companies, leading to a flow of a larger number of units than the actual need, increasing stock and generating stock-outs. Since this phenomenon has been recognized as one of the main obstacles for improving SCN performance, recently it has received a lot of attention by SCN managers and researchers. One of the most common simplifying assumptions in the literature is to assume that the SCN adopts a serial structure. The present work addresses a comparative analysis of the bullwhip effect between a serial SCN and a more complex divergent SCN. To do so, we adopt the framework proposed by Towill et al. (2007), and analyze the response of both SCNs under two different input demands: a stationary demand and an impulse demand. The results reveal that there are not significant differences in terms of bullwhip effect between both SCNs for a stationary demand. Nevertheless, we show how for a violent disturbance in customer demand there is a great different between the two SCNs.

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1. Introduction

The amplification of demand variation in a Supply Chain Network (SCN) is called the bullwhip effect (Lee et al., 1997), and it can be defined as the tendency to see an increase in variability in the replenishment orders with respect to the true demand due to distortion in the demand information as we move upstream in the SCN (Nepal et al., 2012). As consequence, orders placed by upstream nodes exhibit a higher variability as compared to that of orders placed by their downstream partners (Chatfield and Pritchard, 2013). This phenomenon has many undesirable effects such as increasing stock and generating stock-outs (Adenso-Diaz et al., 2012).

The bullwhip effect is relevant both for individual companies that face an unnecessarily variable demand as well as for the entire SCN (Zotteri, 2012). Moreover, the most recent economic downturn has no doubt created a lot of bullwhips around the world (Lee, 2010). For instance, the electronics manufacturing sector has experienced something akin to the bullwhip effect in terms of larger sales declines occurring further upstream (Dvorak, 2009). More specifically, in the last quarter of 2008, consumer demand had declined 8 percent, while product shipments fell 10 percent and chip sales fell 20 percent. These data suggest that electronics retailers, wholesalers and manufacturers responded differently to the decline in consumer demand (Dooley et al., 2010).

Since the bullwhip effect has been long recognized as one of the main obstacles for improving the performance of a SCN, it has received in the last years a lot of attention by managers and researchers (Li, 2012). More specifically, several studies have been generated in the last decade to better understand the causes, economics consequences and remedies to the bullwhip effect. In order to analyze this phenomenon under real business world conditions, increasingly complex mathematical representations of SCNs (such as multi-product scenarios, stochastic lead times, production/distribution capacity constraints, reverse logistic and so on) have been developed. However, several assumptions are commonly made to simplify the analysis (Chatfield and Pritchard, 2013), being one of the most relevant what it can be labeled as a "serial structure model", i.e. each echelon k in the system has a single successor $k+1$ and a single predecessor $k-1$. Undoubtedly, the serial SCN system analysis has represented and continues to represent a powerful technique for studying the dynamics of the bullwhip effect, but this assumption is seldom verified in real SCNs (Bhattacharya and Bandyopadhyay, 2011). The main reason for the adoption of this modeling structure is probably due to the fact that most of the studies dealing with supply chain dynamics are based on classical operational

research methods, continuous time differential equation models, and discrete time difference equation models. Classical operational research methods approaches are not always able to cope with the characteristics of dynamics SCNs (Riddalls et al., 2000; Long et al., 2011). Analogously, continuous time and discrete time difference equation models are not always suitable for analyzing complex supply chain structures outside the serial supply chain, given the high order of differential equations (one tier generally gives a 2nd-4th order system; 2 tiers even 2nd-6th order), which makes analytical analysis difficult (Holweg and Disney, 2005). Essentially, due to the complexity and mathematical intractability of multi-echelon systems, the majority of the literature tends to focus on serial two-echelon systems (Hwarng, 2005).

Nowadays, the increasing challenges of the new generation of SCNs such as those mentioned in Butner (2010), Christopher and Holweg (2011), and Stank et al. (2011), require more realistic models to analyze the increasing complexity of those structures. Hence, there is a need to assess the dynamics of SCNs characterized by more than one member in the same echelon of the chain (Moser et al., 2011; Xuan et al., 2011; Ma et al., 2013). More specifically, in this work we address one of most common adopted SCN structures in the real world, i.e. the divergent or arborescent SCN (Beamon and Chen, 2001). Mineral industries and in general consumer-oriented industries, such as cell phone manufacturers, often adopt this typology of SCN (Hung, 2011). This structure is characterized by a tree-like structure, where every stock point in the system receives supply from exactly one higher echelon stock point, but can supply to one or more lower echelon stock points (Ganeshan, 1999; Hwarng et al., 2005).

The aim of this paper is to analyze the bullwhip effect of a complex SCN. To do so, we perform a comparative analysis between a classical serial SCN with a more complex (divergent) SCN, modeled by means of a multi-agent based-simulation platform named SCOPE. More specifically we firstly reproduce the four-echelon serial SCN structure (i.e. 1 Retailer, 1 Wholesaler, 1 Distributor and 1 Manufacturer) adopted by Chatfield et al. (2004) under identical boundary conditions. Secondly, we generate a new divergent multi-echelon SCN model (i.e. 8 Retailer, 4 Wholesaler, 2 Distributor and 1 Manufacturer) in which each member is furnished by two downstream members. To perform the study we adopt the framework proposed by Towill et al. (2007) for studying the bullwhip effect. In this work, the authors identify three "observer's perspectives" to analyze the bullwhip effect: Variance lens, Shock lens and Filter lens. Basically, this framework suggests the typology of endogenous

input that can be adopted in bullwhip analysis in order to study different characteristics of the SCN. More specifically we adopt two input demand patterns, i.e. the shock lens and the variance 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 latter approach can be viewed as a "crash test" or a "stress test": studying the system performance under an intense and violent solicitation test to determine the resilience of a given SCN structure (Cannella and Ciancimino, 2010).

The computational results reveal that there are not significant differences in term of bullwhip effect between a divergent SCN and a serial SCN for a stationary input in customer demand. However, a violent disturbance in customer demand causes a great different between both SCNs: the divergent SCN is more sensitive to the higher forecast deviations in customer demand caused by this violent disturbance, showing higher variance of orders, taking more time to recover stability, and hence, incurring in higher costs. We can thus conclude that the divergent structure is less robust than the serial structure.

The rest of the paper is organized as follows: Section 2 presents a literature review. Section 3 describes the methodological approach. Section 4 presents the serial SCN and the divergent SCN. Section 5 presents the measurement system and the design of experiments. Section 6 presents the numerical results. Finally, Section 7 and Section 8 present findings, limitations, future directions and conclusions.

2. Literature review

The bullwhip effect is one of the most widely investigated phenomena in the modern day SCN management research (Nepal et al., 2012). The investigation on this phenomenon has passed through diverse phases, from empirical and *ad hoc* studies on bullwhip causes to mathematical approaches to infer on demand amplification solutions. Bullwhip Avoidance Phase in the term coined by Holweg and Disney (2005) to identify the current phase of the studies devoted to the demand amplification phenomenon. One distinctive feature of this phase is the focus on the efficacy of bullwhip solving approaches (Cannella and Ciancimino, 2010). To accomplish this aim, increasingly complex mathematical representations of SCNs have been developed to analyse solving approaches under several scenarios, characterised by

reverse logistic, different forecasting techniques, stochastic lead times, collaborative systems, capacity constraints, batching, parameter configuration, pricing and so on.

Table 1 reports an overview of relevant contributions published during the Bullwhip Avoidance Phase. Articles are classified according to the focus on the parameters and factors investigated (e.g., information sharing, lead time, order policy and demand forecasting), and the typology of SCN structure (e.g. serial and non-serial).

[Table 1 near here]

All aforementioned papers have largely contributed to better understand the causes, economics consequences and remedies to bullwhip. Regardless the adopted methodological approaches, the modelled SCN structure and the metrics used to evaluate the SCN performance, the results have shown how factors such as lead time, the adoption of innovative order policy, specific forecasting techniques and different customer demand patterns can impact on the performance of SCN in terms of demand amplification. However, most of the above-reported studies, in order to quantitatively assess the performance of SCN, have exclusively adopted the classical single echelon structure or the two-stage serial SCN (Bhattacharya and Bandyopadhyay, 2011). In other studies, in order to assess the performance at different level of a multi-echelon system, it has been used the well-know four-echelon "beer-game" (Sterman, 1989) model (i.e. Retailer, Wholesaler, Distributor and Manufacturer). However, even in this case, most of those studies have adopted a classical serial SCN assumption. Essentially, most of the scientific work in SCN dynamics concerns pure retail/distribution chains or serial SCNs with few stages.

We note that there are only few studies based on the non-serial SCN modelling assumption investigating the dynamics of SCNs and demand amplification phenomenon. However, most of these papers do not report any insight on the different dynamics between a classical serial SCN structure and a divergent SCN structure. To the best of our knowledge, the work of Sodhi and Tang (2011) is one of the few papers that have reported some insights on the differences between a serial SCN and a no-serial SCN in terms of their dynamic behaviour. They report anecdotal evidence of how the bullwhip effect increases as the SCN structure becomes more complex in an arborescent SCN due to the increase in the number of echelons, or in the number of successors at each echelon. However, they do not provide any information on the magnitude of this increment. This finding stimulates the need of further structured studies on the quantification of bullwhip effect in no-serial SCNs. In our work, by adopting a

structured framework for studying the bullwhip effect, we also clarify and extend the conclusion by Sodhi and Tang (2011). More specifically, we show how the bullwhip effect is significantly higher for a divergent SCN compared to a serial SCN in the case of a shock in the end customer demand. Meanwhile, the bullwhip magnitude is very similar for both SCNs where customer demand has no shock.

3. Methodological approach

Analytic models, like linear programming, control theory, integer programming and mixed integer programming, are among the most popular approaches for modeling SCNs. However, a SCN is a complex adaptive system that involves dynamics, stochastic, and uncertainty (Sun and Wu, 2005; Surana et al., 2005; Pathak et al., 2007; Wang et al., 2008; Chen, 2012). Unfortunately, analytical models are unable to cope with these characteristics. In addition, analytical models may prove impossible to be solved due to their complexity and nonlinearity (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 their dynamics and stochastic behavior (Chan and Prakash, 2012; Munoz and Clements, 2008). Particularly, multi-agent-based distributed simulation turns out 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; Julka et al., 2002; Dong et al., 2006; Chatfield et al., 2001; Govindu and Chinnam, 2010; Long et al., 2011; Chatfield et al., 2013; and Chatfield, 2013 among others). A simulation architecture that is able to both view a complex SCN and examine various causes and their effects at the same time would provide new insight to the various forces and influences in a SCN (Alony and Munoz, 2007).

SCOPE is an agent-based SCN simulator described in Cañizares and Framinan (2012) for modeling and simulating different processes taking place in SCN management, focusing in the Order Fulfilment Process and allowing an easy model of real scale SCN. Every company in the model can be set up with different policies and parameter values for the different business functions. 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 and 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 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. Figure 1 shows the framework of SCOPE.

[Figure 1 near here]

Cañizares and Framinan (2012) validated SCOPE by comparing the results obtained by other authors in the literature using different methodologies. More specifically, they followed the same steps followed by Chatfield et al. (2004) to validate SISCO, a software built by the authors to simulate the storage, modeling, and generation of SCNs for Integrated Supply Chain Operations. In SISCO, the user specifies the structure and policies of a SCN using a Graphical User Interface (GUI) based application, and then saves the SCN description in the open eXtensible Markup Language (XML) based Supply Chain Modeling Language (SCML) format. SISCO automatically generates the simulation model when needed by mapping the contents of the SCML file to a library of supply-chain-oriented simulation classes. The validation of SISCO consisted of modeling a simple serial four-stage SCN and comparing its results (in terms of amplification of the standard deviation of orders) with the results obtained by two well-know authors: Chen et al. (2000), employing a statistical approach, and Dejonckheere et al. (2003), employing a control engineering approach. Table 2 shows a comparison between SISCO and SCOPE with the experiments of Chen et al. (2000). In view of these results, we can conclude that SCOPE can be considered a validated platform for the subsequent computational experience.

[Table 2 near here]

4. Supply Chain Network employed as Testbed

The serial SCN modeled is that of Chatfield et al. (2004), consisting of four echelons: one factory, one distributor, one wholesaler, and one retailer (Figure 2). The lower node places orders to the 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).

A divergent SCN is characterized by a tree-like structure, where every stock point in the system receives supply from exactly one higher echelon stock point, but can supply to one or more lower echelon stock points (Hwarng et al., 2005). The divergent SCN is modeled following the next two guidelines:

1. In order to benchmark both SCNs and to isolate the main effects, the divergent SCN has to be analogous to the serial SCN of Chatfield et al. (2004). Hence, the resultant SCN should have identical values of parameters, number of stages (horizontal complexity) and, due to the divergent topology, an increasing number of nodes per stage (vertical complexity), maintaining the symmetry of the SCN.

2. Due to the prospective nature of this work, the resultant divergent SCN must have the minimum complexity. To fulfill with all requirements, each node in the SCN supplies just two nodes downstream.

The divergent SCN obtained is shown in conjunction with the serial SCN in Figure 2. The characteristics described in Chatfield et al. (2004) for the serial SCN are adapted to the divergent SCN as follows:

- **Customers Demand**. Each customer demand follows the same normal distribution with mean μ_{O_C}, estimated by $\overline{D}_{O_C}$, and variance $\sigma^2_{O_C}$, estimated by $s^2_{O_C}$.

- **Lead Time**. The lead time, L, is stationary and independently and identically distributed with mean μ_L estimated by $\overline{L}$, and variance σ^2_L estimated by s^2_L . 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 et al. (2004), 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 is $L+R$. The mean lead time is 4 time units for all nodes in the SCN (not including the review period, R=1), and 0 for customers. These delays are gamma-distributed, with a coefficient of variation $c.v. = 0.50$.

- **Lead-Time Demand**. Let X^t_{ij} be the demand received by node j in 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_X^2 that we estimate by $s_{X_{ij}^t}^2$. Denoting by D_{ij}^{t+k} the demand received by node j in stage i at time $t + k$, we obtain X_{ij}^t for an order placed at time t by the convolution:

$$X_{ij}^t = \sum_{k=0}^{L+R} D_{ij}^{t+k} \tag{1}$$

- **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 $L+R$:

$$S_{ij}^t = \bar{X}_{ij}^t + z s_{X_{ij}^t} \tag{2}$$

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. The term $s_{X_{ij}^t}$ is an estimation of the standard deviation of X_{ij}^t, and the safety factor used is $z = 2.0$ (service level of 97.72%) , according to Chatfield et al. (2004). 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 to the lead time data from previous periods (used to forecast the expected lead time at time period t, $\bar{L}_{ij}^t$), and finally uses this information to generate forecasts of lead-time demand mean $\bar{X}_{ij}^t$ and variance $s_{X_{ij}^t}^2$, as indicated in (3) and (4), respectively:

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

$$s_{X_{ij}^t}^2 = (\bar{L}_{ij}^t + R)s_{O_{ij}^t}^2 \tag{4}$$

To estimate $(\bar{D}_{ij}^t, s_{O_{ij}^t}^2)$, according to Chatfield et al. (2004), each node uses a p-period moving averages ($MA(p)$) and a p-period moving variances ($MV(p)$) with $p=15$. To estimate $(\bar{L}_{ij}^t)$, each node uses running averages, which utilizes data available from all previous periods.

- **Reverse Logistic**. With the exception of the 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 the 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 the S_{ij}^t level.

  3. Receive products from the upstream node.

  4. Receive new orders from the downstream nodes and satisfies demand.

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

[Figure 2 near here]

5. Metrics and experiments design

First proposed by Chen et al. (2000), the Order Rate Variance Ratio (Φ) is the most widely used indicator to detect the bullwhip effect (Cannella et al., 2013), measuring the internal process efficiency and showing the performance of each node in the SCN. It is a demand-independent measure, allowing the comparison between different SCNs. Nevertheless, measuring the internal process efficiency at the individual level (single echelon) is insufficient as it only accounts for the individual performance of each link in the chain separately (Cannella et al., 2013). Therefore, a network measure has to be used as a complementary measure of Φ. The Bullwhip Slope (*BwSl*) summarizes all the ratios obtained for each stage in a single measure, allowing a complete comparison between different SCNs at the network level (Ciancimino et al., 2012; Cannella et al., 2013). The procedure to calculate this metric is to perform a linear regression on the values of Φ using the echelon position as independent variable (equation 6). A high value of the slope means a fast propagation of the bullwhip effect through the SCN, while a low value means a smooth propagation. Since *BwSl* is a synthesis of Φ, there are similar costs associated to this metric (procurement, overtime and subcontracting) but at the network level. Below, these two metrics are summarized.

- Order Rate Variance Ratio of a node i (Φ_i): computed as the ratio of the order variance in a generic node ($\sigma^2_{O_i}$, estimated by $s^2_{O_i}$) to the order variance of the end customer demand (σ^2_d, estimated by s^2_d).

$$\Phi_i = \frac{s^2_{O_i}}{s^2_d} \tag{5}$$

- *BwSl*: computed as the slope of the linear regression of the Φ curve.

$$BwSl = \frac{K \sum_{i=1}^{K} p_i \Phi_i - \sum_{i=1}^{K} p_i \sum_{i=1}^{K} \Phi_i}{K \sum_{i=1}^{K} p_i^2 - \left(\sum_{i=1}^{K} p_i\right)^2} \tag{6}$$

Being K the total number of echelons and p_i the position of the ith echelon.

The above mentioned metrics are easy to apply to a serial SCN, but there is one important difference when applying them to a divergent SCN, as each stage contains, in general, more than one node. In the serial SCN, the parameter required to compute the different metrics on each stage (i.e. the order variance) is taken from the only node in the stage. In the divergent SCN, it is necessary to find an aggregate measure for the whole stage. 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 the stage i: $AO_i = \sum_{j=1}^{n_i} O_{ij}$, being n_i the number of nodes in the 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}), and Φ_i is:

$$\Phi_i = \frac{s^2_{AO_i}}{s^2_{Ad}} \tag{7}$$

In view of the fact that all the customer demands are assumed to be independent and that each node places orders independently, the aggregate variance in each stage i is the sum of the variances of orders of each node j in the 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 Φ_i:

$$\Phi_i = \frac{\sum_{j=1}^{n_i} s^2_{O_{ij}}}{\sum_{j=1}^{n_C} s^2_{O_{Cj}}} \tag{8}$$

Chatfield et al. (2004) analyze the impact of stochastic lead times, information quality and information sharing on the performance of SCNs, carrying out a factorial experiment utilizing these three indicators. For the comparison between the serial and the divergent SCNs, we have taken the following values of these factors from their factorial experiment: lead time coefficient of variation $c.v. = 0.50$; no information sharing; quality of information utilized for updating the S level shown in equations (3) and (4) (named IQL1 by Chatfield et al., 2004). These factors remain fixed in our experiments.

For the bullwhip analysis, we adopt the framework proposed by Towill et al. (2007) (see Section 1). Attending to the variance lens perspective, the demand pattern is the same as in Chatfield et al. (2004), i.e. demands follows a $N(50, 20^2)$ distribution. Attending to the shock lens perspective, we use a $N(50, 20^2)$ distribution, which suffer an average increment of 100% in the middle of the simulation time (not considering the warm-up period, see below), turning into a $N(100, 20^2)$. These demand patterns are applied to the only customer in the serial SCN, and to every customer in the divergent SCN.

We design two sets of experiments: the stationary response set and the dynamic response set. In the stationary response set, in order to compare the performance of the serial and the divergent SCNs under both lenses, a global measure of Φ and *BwSl* are obtained for both demand patterns. In the dynamic set, the temporal evolution of Φ is obtained under the shock lens in order to analyze the impulse response of both SCNs in detail.

In the first set of experiments, a simulation experiment has been carried out for each SCN and for each demand pattern. Following the simulation procedure indicated in Chatfield et al. (2004), each experiment consists in 30 replications of 700 periods, with the first 200 periods of each replication removed as a warm-up used to set up the system. The results obtained from the replications are averaged for each experiment. To be able to compare the experiments under both lenses, metrics are calculated in the same simulation period, after the impulse time (*t*=450). The first set of experiments is summarized in Table 3.

[Table 3 near here]

In the second set of experiments, in order to obtain the temporal response, each SCN is evaluated in different simulation periods. In the first observation, named *T*0, SCNs are simulated until the simulation time is just before the demand impulse occurs, obtaining the initial Φ. Then, Φ is measured in a sequence of experiments where the simulation time starts at the demand impulse instant and the simulation time is increasing in intervals of 25 or 50

periods until the end of the original simulation time is reached (t=700), resulting in the experiments $T1$-$T6$. As for the first set, each experiment consists in 30 replicates, and the results obtained are averaged. This set of experiments is summarized in Table 4.

[Table 4 near here]

6. Numerical Results

6.1. *Stationary response set*

Under the variance lens, results obtained for Φ are very similar for both SCNs (see Figure 3), being slightly higher for the divergent SCN at the upper stages. However, under the shock lens there is an important difference between both SCNs, as Φ is considerably higher for the divergent SCN (see Figure 4). The average results for Φ and *BwSl,* as well as the differences between both SCNs ($\Delta(\%) = \frac{\Phi_{\ Divergent} - \Phi_{\ Serial}}{\Phi_{\ Serial}} * 100\%$) are shown in Table 5, together with the corresponding 99%-confidence intervals.

Under the variance lens, it can be seen that the values of the measures are not statistically different, which indicates a rather similar performance for both SCNS. At the lower stages, the increase of Φ is below 1%, while at the upper stages the differences are slightly higher (Φ is 5.39% higher for the divergent SCN at the distributor stage and 6.08% at the factory stage). *BwSl* helps to easily compare both SCNs. The propagation of the bullwhip effect is very similar for both SCNs, being slightly higher (6.20 %) for the divergent SCN.

[Figure 3 near here]

[Figure 4 near here]

Under the shock lens, the Φ curve is clearly stepped for the divergent SCN, with the minimum increase at the retailer stage (1.32% over the serial SCN) and the maximum increase at the factory stage (95.86% over the serial SCN). The bad performance of the divergent SCN in this case is well summarized by the value of *BwSl*, being 94.62% higher than in the serial SCN. Note that the differences in the indicators for both SCNs are statistically different, thus confirming that the divergent SCN performs worse than the serial SCN in this scenario.

[Table 5 near here]

6.2. *Dynamic response set*

Figure 5 shows the evolution of Φ over time for each stage after the demand impulse (rhomboids dots for the serial SCN and square dots for the divergent SCN). The differences

for Φ observed between both SCNs in Figure 5 are plotted in Figure 6, showing the temporal evolution of $\Delta(\%)$ for each stage. Under an unexpected impulse in demand average:

- Both SCNs react by: 1) immediately incrementing their order variances in all stages, and 2) decreasing their order variances over time.

- The highest increase in Φ takes place just after the demand impulse ($T1$). The difference between both SCNs is maximal at this point, being higher as we move upstream (see Figure 6).

- The shock recovery is similar for both SCNs at the lower stages (retailers and wholesalers), whereas $\Delta(\%)$ is near to zero after $T3$ (see Figure 6). However, at the upper stages (distributors and factory), shock recovery is slower for the divergent SCN, obtaining high values of $\Delta(\%)$ until the end of the simulation time ($T6$).

[Figure 5 near here]
[Figure 6 near here]

In Figure 7, the order pattern at the factory stage is plotted against the customer order pattern for both SCNs under the shock lens. It is easy to see the high overreaction of the divergent SCN when the demand impulse occurs.

[Figure 7 near here]

Finally, a sensitivity analysis has been performed by systematically increasing the level of end customer standard deviation in the shock lens part of the simulation. The results show that as the impulse in customer demand variability increases, standard deviation of the orders placed in the lower echelons does not increase at the same rate. For example, 47.49% increase in customer demand standard deviation in the shock lens, resulted a 25.96% increase in the standard deviation of the factory orders. In other words, the increase in the shock was transmitted in lower proportions towards the upstream levels of the supply chain.

7. Findings and managerial implications

The results obtained in the previous section give new insights on the bullwhip effect research topic, considering two different lenses for the comparison of two different SCN structures. Under the variance lens, the following comments can be done:

- The bullwhip effect found in the serial and the divergent SCNs are very similar. When the demand is predictable and the nodes can adequately adjust their inventory levels to

fulfill the demand with a high customer service level, both SCNs are quasi-equivalents. A node at the stage i of the divergent SCN causes the same amplification of orders that a node in the same stage i of the serial SCN, because they have the same order-up-to and forecast policies. The orders received by each node are proportional to the end customer demand, and hence, to the amplification of orders caused by them. As the variance of orders in each stage is rated to the end customer demand variance, each stage produces similar values of Φ for both SCNs.

- The small increase observed in Φ for the divergent SCN in Figure 3 is caused by eventual excess of stock or by eventual stock-outs. Due to the uncertainties in the end customer demand and lead times, sometimes either the demand received may be different than the demand forecasted in the previous period, or the orders arrive earlier or later than expected, causing this phenomenon. In these cases, where the inventory level is far from the desired order-up-to level, a node reacts by ordering a big quantity of products (a positive order in case of stock-out and a negative order in case of excess of inventory). These exceptionally high orders are amplified upstream, increasing the variance ratio mainly in the upper stages. In view of the fact that for each node there is a certain probability that this phenomenon occurs, and that the divergent SCN has a higher number of nodes in each stage (higher vertical complexity), it happens more frequently in the divergent SCN, causing the little increment in the values of Φ at the upper stages (distributor and factory). As a summary, we can conclude that the divergent SCN has almost the same performance in terms of bullwhip effect than the serial SCN when the end customer demand does not suffer important changes.

Using the shock lens, the following comments can be done:

- Under the shock lens both SCNs are stress tested. The end customer demand impulse causes a massive stock-out situation at the retailer stage, which is then propagated and amplified along the SCN, causing stock-outs in all the stages of the SCNs. While the factory in the serial SCN has to manage the instability caused by the stock-out of one retailer, the same factory in the divergent SCN has to manage it with the stock-outs of eight retailers. The disproportional orders of the factory and distributors in the divergent SCN can be observed in Figure 7, and are the cause of: the excess of variance observed in Figure 4, the high peaks of variances, and the slow recovery observed in Figure 5.

- The divergent SCN has a bad performance as compared to the serial SCN under important unpredicted changes in demand tendencies. We can thus conclude that divergent SCNs are less robust than serial SCNs.

It is worth mentioning the relevance of the framework for the analysis of the bullwhip effect proposed by Towill et al. (2007). The authors stated that "the detection of bullwhip effect depends on which lens is used", and they proposed three different lenses for bullwhip analysis (variance, shock and filter lens). Our experiments have shown different behaviors depending on the lens used: while for the classical variance lens analysis (stationary stochastic demand input) the bullwhip effect is similar for both SCNs, the shock lens analysis (step demand input) reveals that the divergent SCN performs worse than the serial SCN.

With respect to the managerial implications of the study, to face up with the less robustness of divergent SCNs, managers may find useful to consider the following:

- Under a shock in end customer demand, the bullwhip effect increases when the SCN structure becomes more complex as the number of echelons increases, or as the number of successors at each echelon increases. Thus, to mitigate this incremental bullwhip effect, a firm could consider simplifying the SCN structure by reducing the number of echelons or by reducing the number of successors (Sodhi and Tang, 2011). This is particularly important for SCNs characterized by high variations in the end customer demand. On the contrary, traditional arborescent SCNs operaing in markets characterized by a stable consumer demand are less prone to the detrimental consequences of the demand amplification phenomenon.

- An adequate forecast method adjusted to the end customer demand would prevent the firm from eventual excess of stock or from stock-outs. Therefore, it is important to make an effort to implement techniques in order to better understand the end customer demand tendencies (i.e. surveys) and to anticipate important changes.

- The implementation of well-known techniques for reducing the bullwhip effect (i.e. information sharing) is highly desirable. These techniques may help managers to have a better control of the bullwhip effect in case of important changes in the end customer demand that cannot be anticipated by the above techniques. However, it has yet to be proved how these techniques (usually tested in serial SCNs) perform in non-serial SCNs.

8. Conclusions

The literature review has revealed a lack of research on the bullwhip effect topic when the structure of the SCN is different than a serial SCN. However, real SCNs rarely adopt a traditional serial structure, often following a more complex topology. The present work is a first attempt to cover this research gap by analyzing the bullwhip effect in a divergent SCN and by comparing its performance with those of a serial SCN already analyzed in the literature by several authors. This analysis has been carried out using the variance lens and the shock lens proposed by Towill et al., (2007). The bullwhip effect has been observed both from a static and a dynamic perspective, being measured at the node level by the Order Rate Variance Ratio (which has been adapted to the divergent SCN), and at the network level by the Bullwhip Slope.

The main result obtained show that divergent SCNs are more sensitive to unexpected violent changes in demand signal than serial SCNs. Two situations have been considered:

- Variance lens, i.e. stationary demand signal. In this case the performance of both SCNs is very similar, being just a little worse for divergent SCNs.
- Shock lens, i.e. demand signal suffers an unexpected violent change. In this case the performance of the divergent SCN is much worse than that of the serial SCN, showing higher variance of orders and taking more time for recovery, incurring in higher costs.

Bhattacharya and Bandyopadhyay (2011) indicated that there are operational and behavioral causes of the bullwhip effect, and that the root of all the causes is the lack of coordination among the SCN members. Our paper shows that there are also structural factors that amplify the bullwhip effect caused by those operational and behavioral factors.

Our study is of an exploratory nature since this topic that has not been previously addressed. Therefore we have tried to not add excessive complexity that may obscure the interpretation of the results. This comes at the price of a number of limitations that have been identified and that constitute future research lines. Some of these are:

- The present work is limited by fixed operational factors (order-up-to policy, forecasting, etc.) and by the SCN structure itself. As underlined by Dejonckheere et al. (2004), more or less bullwhip could be obtained by selecting other vectors of parameters. A deeper analysis must be done to better understand this type of SCNs,

considering different operational factors and structural factors (horizontal and vertical complexity).

- The less robust structure of the divergent SCN might be compensated by a good information system, in order to share end customer demand (information sharing) and current inventory levels (synchronized supply, see Cannella and Ciancimino, 2010; Ciancimino et al., 2012), allowing a faster and proportional response to violent changes in the end customer demand. Such information system can be adapted to divergent SCNs and its efficiency tested.

- It has been shown that, in addition to the number of stages, other structural factors may influence the bullwhip effect. An identification of these factors and a quantification of their effects could be done.

Acknowledgments

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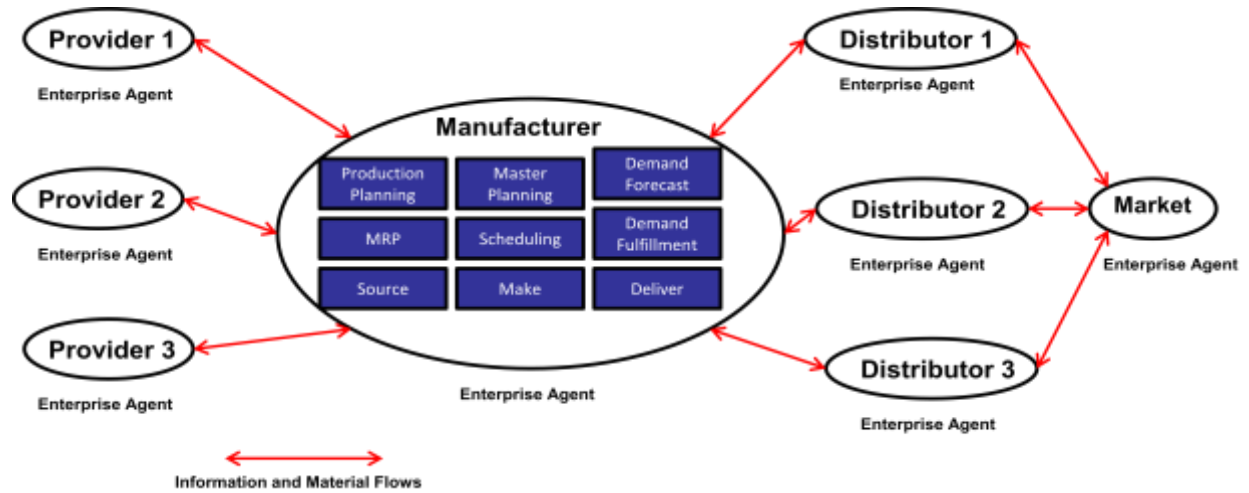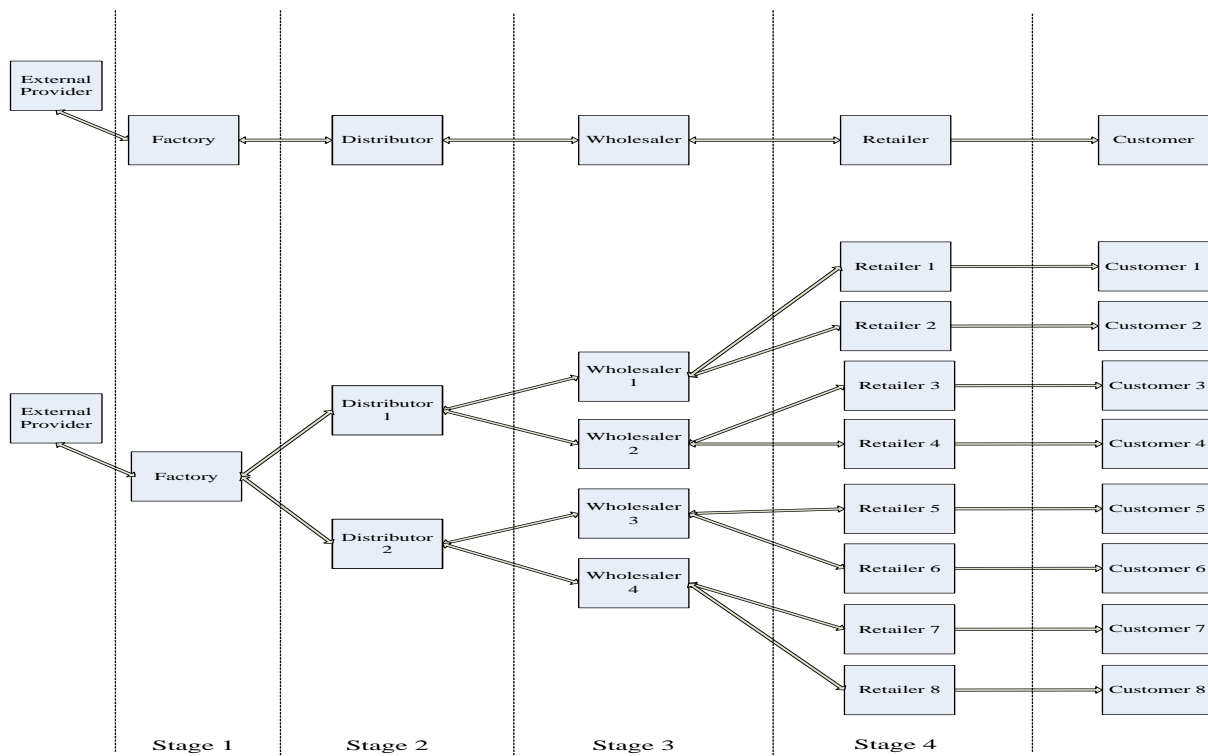
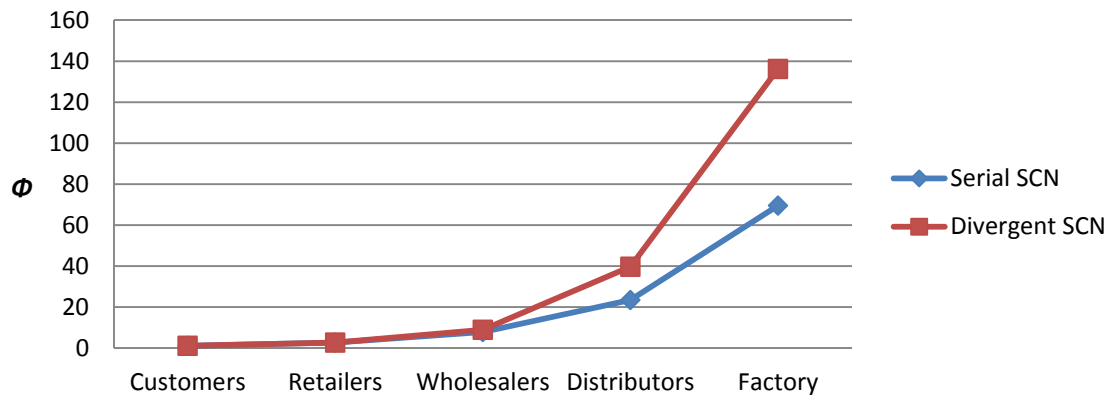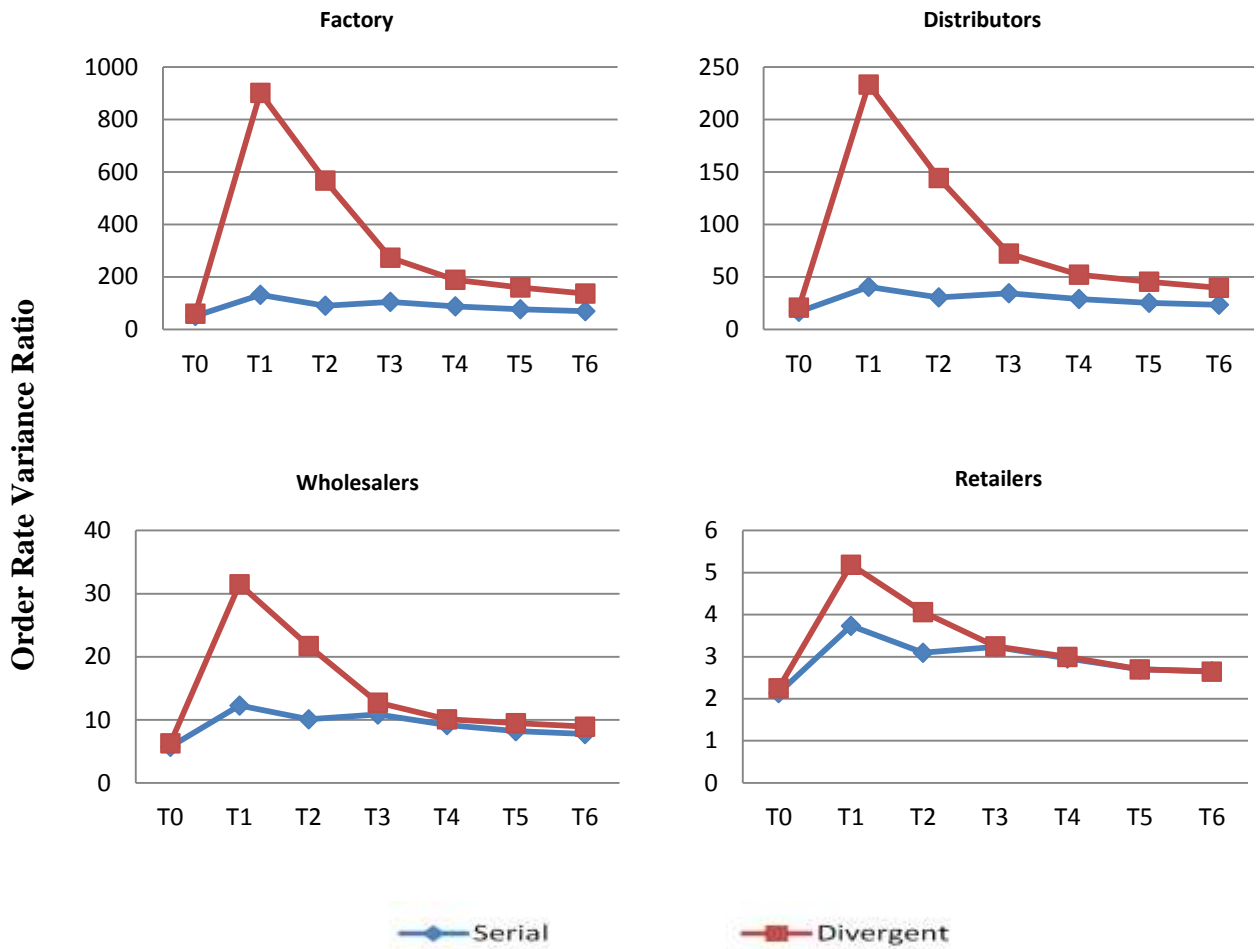**Figure 1**: Multi-Agent Framework of SCOPE.
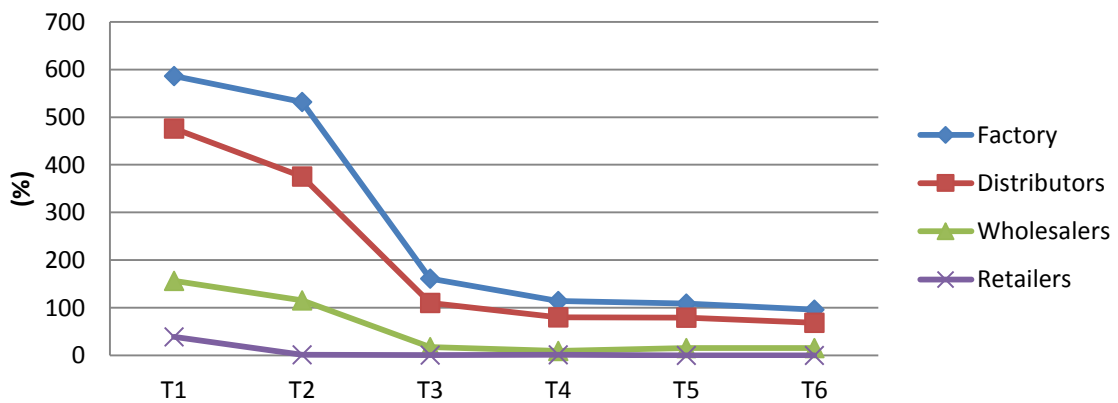

Figure 2. Serial vs Divergent SCNs.
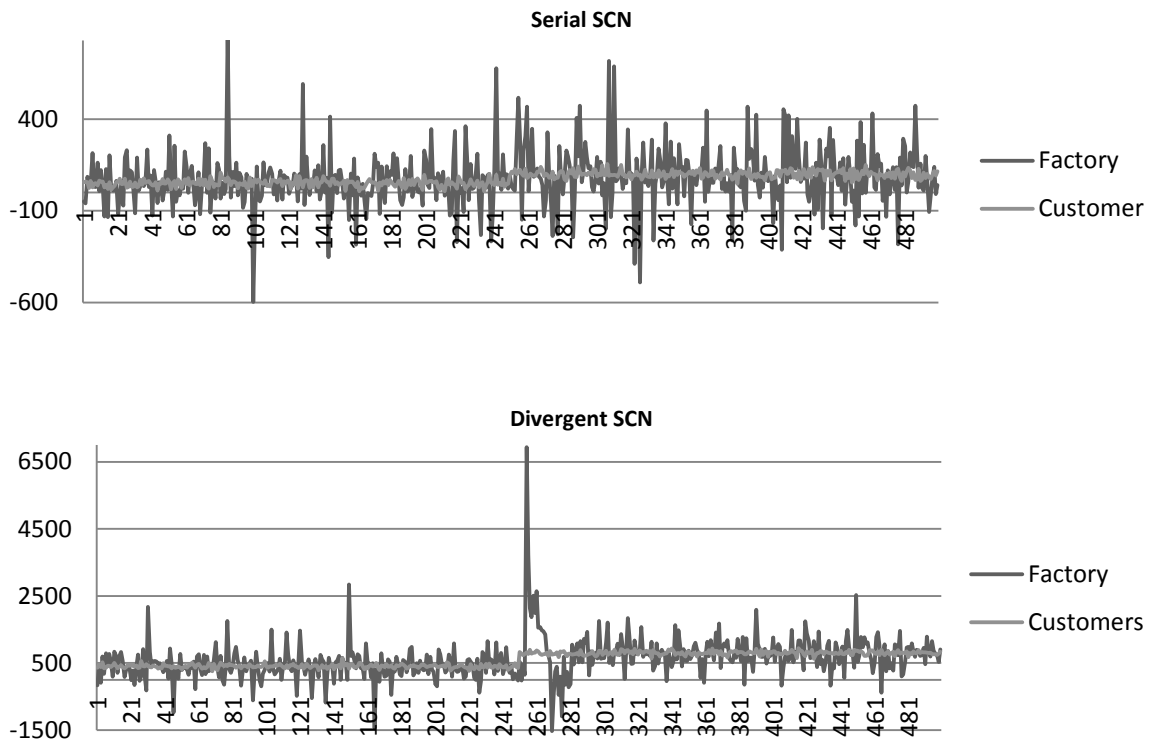
Figure 3. Φ under the Variance Lens.

Figure 4. Φ under the Shock Lens.

Figure 5. Evolution of *Φ* over time under the Shock Lens.

Figure 6. Divergent SCN *Φ* increments over the serial SCN.

Figure 7. Factory vs end customer demand order patterns under the shock lens.

Table 1. An overview of relevant contributions published during the Bullwhip Avoidance Phase.

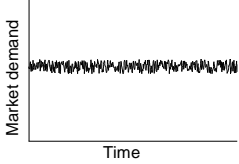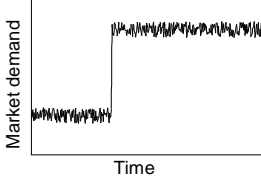|	Chen et al. (2000)	Cachon and Fisher (2000)	Dejonckheere et al. (2002)	Disney and Towill (2003a)	Disney and Towill (2003b)	Dejonckheere et al. (2003)	Chatfield et al (2004)	Dejonckheere (2004)	Disney et al. (2004a)	Disney et al. (2004b)	Machuca and Barajas (2004)	Shang et al. (2004)	Warburton (2004)	Zhang (2004)	Chandra and Grabis (2005)	Gonçalves et al. (2005)	Ingalls et al. (2005)	Byrne and Heavey (2006)	Disney et al. (2006)	Hosoda and Disney (2006a)	Hosoda and Disney (2006b)	Kim et al. (2006)	Lalwani (2006)	Villegas and Smith (2006)	Ouyang and Daganzo (2006)	Zhou and Disney (2006)	Boute et al. (2007)	Chen, Disney (2007)	Disney et al. (2008)	Hosoda et al.(2008)	Jakšič and Rusjan (2008)
Information sharing	■	■				■	■					■						■				■		■					■	■	
Lead Time		■				■			■	■									■	■						■					
Order Policy			■	■	■		■	■	■		■	■		■	■		■			■	■	■	■		■	■	■	■			■
Forecast	■		■	■	■		■	■				■				■		■		■	■									■	
Non-Serial		■																						■							
Serial	■		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■		■	■	■	■	■	■	■

	Kim, Springer (2008)	Aggelogiannaki et al.(2008)	Caloiero et al. (2008)	Kelepouris et al. (2008)	Wright and Yuan (2008)	Agrawal et al. (2009)	Chen and Lee (2009)	Cannella and Ciancimino (2010)	Chaharsooghi and Heydari (2010)	Yuan et al. (2010)	Bottani and Montanari (2010)	Ouyang (2010)	Sari (2010)	Hussain and Drake (2011)	Ali and Boylan (2011)	Dass and Fox (2011)	Barlas and Gunduz (2011)	Cannella et al. (2011)	Yang et al. (2011)	Sodhi and Tang. (2011)	Kristianto et al. (2012)	Adenso-Diaz et al. (2012)	Hussain et al. (2012)	Cannella et al. (2012)	Nepal et al.(2012)	Chen et al. (2012)	Ciancimino et al. (2012)	Su and Geunes (2012)	Chatfield and Pritchard (2013)	Cho and Lee (2013)	Garcia Salcedo et al. (2013)	Li and Liu (2013)
Information sharing			■		■		■			■							■	■								■					■	
Lead Time	■			■				■	■					■		■			■			■			■	■		■	■		■	■
Order Policy	■	■	■	■	■		■	■	■				■					■					■	■					■		■	■
Forecast			■	■	■					■												■		■	■	■	■					
Non-Serial												■				■				■						■						■
Serial	■	■	■	■	■	■	■	■	■	■	■		■	■	■		■	■	■	■			■	■	■		■	■	■	■	■	
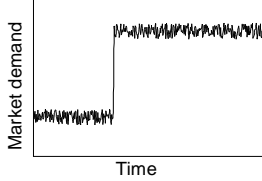
Table 2: Validation of SCOPE

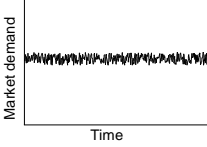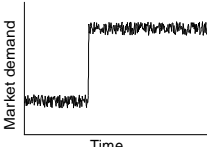| Echelon	Chen et al. (2000)	Chatfield et al. (2004) SISCO	Cañizares and Framinan (2012) SCOPE
Retailer	1.89	1.90	1.90
Wholesaler	3.57	3.59	3.53
Distributor	6.74	6.70	6.66
Factory	12.73	12.84	12.58

Table 3. Stationary response set of experiments.

Bullwhip Effect Lens	Demand Pattern	Structure of the SCN	Metrics
Variance Lens	$N(50, 20^2)$ $t \in [0\text{-}700]$	Serial SCN	Φ $BwSl$ $t \in [450\text{-}700]$
		Divergent SCN	
Shock Lens	$N(50, 20^2)\ t \in [0\text{-}449]$ $N(100, 20^2)\ t \in [450\text{-}700]$	Serial SCN	
		Divergent SCN	

Table 4. Dynamic response set of experiments.

Bullwhip Effect Lens	Demand Pattern	Simulation Periods	Structure of the SCN	Metrics
Shock Lens	$N(50, 20^2)$ $t \in [0\text{-}449]$ $N(100, 20^2)$ $t \in [450\text{-}700]$	$T0$: [200-449]	Serial/Divergent	Φ
		$T1$: [450-475]	Serial/Divergent	
		$T2$: [450-500]	Serial/Divergent	
		$T3$: [450-550]	Serial/Divergent	
		$T4$: [450-600]	Serial/Divergent	
		$T5$: [450-650]	Serial/Divergent	
		$T6$: [450-700]	Serial/Divergent	

Table 5. Numeric results for Φ and *BwSl*.

Lens	SCN structure	Φ				BwSl
		Retailer	**Wholesaler**	**Distributor**	**Factory**	
Variance Lens 	Serial	2.253±0.0308	6.329±0.1766	19.153±0.7367	57.766±2.6669	13.043±0.603
	Divergent	2.258±0.0289	6.331±0.1695	20.186±7626	61.276±2.6517	13.852±0.603
	Δ(%)	**0.222**	**0.032**	**5.393**	**6.076**	**6.203**
Shock Lens 	Serial	2.655±0.0126	7.732±0.1203	23.453±0.4962	69.539±1.7386	15.790±0.394
	Divergent	2.690±0.0119	8.923±0.1188	39.595±0.8211	136.196±2.8934	30.730±0.654
	Δ(%)	**1.318**	**15.404**	**68.827**	**95.856**	**94.617**