European Journal of Operational Research 243 (2015) 120–129

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Production, Manufacturing and Logistics

The effect of Inventory Record Inaccuracy in Information Exchange Supply Chains

Salvatore Cannella[a,b,*], Jose M. Framinan[a], Manfredi Bruccoleri[c], Ana Paula Barbosa-Póvoa[d], Susana Relvas[d]

[a] *Industrial Management & Business Administration Department, School of Engineering, University of Seville, Spain*
[b] *School of Industrial Engineering, Pontificia Universidad Católica de Valparaíso, Valparaiso, Chile*
[c] *Department of Chemical, Management, Mechanical Engineering and Computer Science, Faculty of Engineering, University of Palermo, Italy*
[d] *Centre for Management Studies, Instituto Superior Técnico, Technical University of Lisbon, Portugal*

ARTICLE INFO

Article history:
Received 29 June 2013
Accepted 11 November 2014
Available online 28 November 2014

Keywords:
Supply chain management
Information sharing
Collaboration
Bullwhip effect
System dynamics

ABSTRACT

The goal of this paper is to quantify the impact of Inventory Record Inaccuracy on the dynamics of collaborative supply chains, both in terms of operational performance (i.e. order and inventory stability), and customer service level. To do so, we model an Information Exchange Supply Chain under shrinkage errors in the inventory item recording activity of their nodes, present the mathematical formulation of such supply chain model, and conduct a numerical simulation assuming different levels of errors. Results clearly show that Inventory Record Inaccuracy strongly compromises supply chain stability, particularly when moving upwards in the supply chain. Important managerial insights can be extracted from this analysis, such as the role of 'benefit-sharing' strategies in order to guarantee the advantage of investments in connectivity technologies.

1. Introduction

The Operations Management community has been identifying Supply Chain (SC) collaboration practices as some of the most effective approaches for limiting SC inefficiencies such as bullwhip effect (Lee, 2010; Lee, Padmanabhan, & Whang, 1997). Information sharing is at the core of collaborative, SC based business models (Cannella, Barbosa-Povoa, Framinan, & Relvas, 2014; Fawcett, Osterhaus, Magnan, Brau, & McCarter, 2007). The concept of information sharing may be used in terms of access to information about the exact physical location of goods en route from supplier to customer at a particular moment (Jonnson & Mattsson, 2013). Depending on the information shared by firms and on how this information is used, different typologies of SC collaboration practices can be realized. For instance, if members share real-time sharing of market demand data for the generation of conjoint forecasting, they can implement a collaborative supply chain structure known in literature as Information Exchange SC (Holweg, Disney, Holmström, & Småros, 2005). This structure has been shown to be able to remove harmful problems resulting from information distortion (Ali & Boylan, 2011; Ali, Boylan, & Syntetos, 2012; Agrawal, Sengupta, & Shanker, 2009; Cannella, 2014; Cannella & Ciancimino, 2010; Dejonckheere, Disney, Lambrecht, & Towill, 2004; Disney et al., 2004; Holweg et al., 2005; Machuca & Barajar, 2004; Trapero, Kourentzes, & Fildes, 2012; Wong, Lai, & Cheng, 2014; Yuan, Shen, & Ashayeri, 2010). However, as the effectiveness of an inventory management system depends on the quality of information used (Ketzenberg, Geismar, Metters, & van der Laan, 2012), inventory accuracy can be reasonable considered one key aspect to ensure the benefits of the Information Exchange SC. Clearly, even if members benefit from up-to-date information on customer demand, various problems may arise if they manage their stock by using policies that assume perfect information on inventory positions, despite system-reported inventory inaccuracies (Bai, Alexopoulos, Ferguson, & Tsui, 2012). More specifically, if the recorded inventory quantity does not match the actual quantity in the shelf, the system will either order unnecessary items, or fail short of orders (DeHoratius & Raman, 2008; Rekik, 2011 ; Rekik, Sahin, Jemai, & Dallery, 2008a; Sahin, Buzacott, & Dallery, 2009; Sarac, Absi, & Dauzre-Prs, 2010). This dysfunction is known in literature as "Inventory Record Inaccuracy" (IRI). The effects of IRI are numerous and can put at risk the financial performance of a firm through diverse factors such as: lost sales, delay penalties, re-scheduling, suboptimal planning and increase in use of small transport vehicles amongst others (Thiel, Hovelaque, & Thi Le Hoa, 2010). In the present day, the difference between physically inventory level and system inventory level is not sufficiently understood to explain or predict its effect on performance (Nachtmann, Waller, & Rieske, 2010; Rekik, 2011; Rekik & Sahin, 2012;

* Corresponding author Tel.: 00393386263359..
E-mail addresses: cannella@us.es (S. Cannella), framinan@us.es (Jose M. Framinan), manfredi.bruccoleri@unipa.it (M. Bruccoleri), apovoa@ist.utl.pt (A. P. Barbosa-Póvoa), susana.relvas@ist.utl.pt (S. Relvas).

http://dx.doi.org/10.1016/j.ejor.2014.11.021
0377-2217/© 2014 Published by Elsevier B.V.

Rekik, Sahin, & Dallery, 2008b). However, inventory inaccuracy appears to be a significant problem in practice (Kang & Gershwin, 2005, Heese, 2007, Uçkun, Karaesmen, & Savas, 2008, Sahin & Dallery, 2009, Hollinger & Adams, 2010, Xu, Jiang, Feng, & Tian, 2012, Hardgrave, Aloysius, & Goyal, 2013, Mersereau, 2012, Metzger, Thiesse, Gershwin, & Fleisch, 2013, Bruccoleri, Cannella, & La Porta, 2014)

In an empirical investigation, DeHoratious & Raman (2008) observed inaccuracies of 65 percent on 369.567 inventory records collected from 37 leading retailers in USA. In their study, they conclude that these inaccuracies do not only affect retailers' operational performance, but also that of upstream supply chain partners (Kwak & Gavirneri, 2014). Inaccuracies and their eventual correction are likely to increase the bullwhip effect by increasing the variability of orders (Gel, Erkip, & Thulaseedas, 2010, Bruccoleri et al., 2014). The inventory error will propagate through the entire supply chain (Dai & Tseng, 2012). In fact, as shown by Kök and Shang (2014), when an echelon in the SC suffers an IRI problem, it generates orders characterized by a higher variability with respect to orders based on accurate inventory information. These orders are transmitted to the supplier and also impact on its inventory management (Kwak & Gavierneri, 2014). This is mainly because the forecast on the incoming demand from downstream stages of the chain is used by the supplier for setting his/her levels of inventory. Essentially, it is expected that the increased variability of the total demand due to IRI will be transferred from the retailer to the manufacturer (Xu et al., 2012). Thus, inventory loss across locations in a supply chain is a factor that may contribute to the bullwhip effect (Kok & Shang, 2014). This increased variability in the order can generate a negative impact not only in a traditional SCs, but also in collaborative structures in which members share real-time sharing of market demand. For instance, in the Information Exchange SC, even if an upstream member of the supply chain accesses to and benefits from updated information on customer demand, she continues to use the information of orders placed by the downstream stages for the management of her inventory requirements. Thus, she continues to be exposed to a high variability of incoming order, and consequently to a distorted information. This "phantom demand" (Min & Zhou, 2002) caused by the "phantom inventory" (Hardgrave et al., 2013), can undermine the expected benefit of information sharing and the effort in IT investment.

Moreover, IRI problems can occur for each echelon of a multi-echelon inventory system instead of a single echelon (Gumrukcu, Rossetti, & Buyurgan, 2008). Transaction errors (i.e. shipment errors, delivery errors, scanning), shrinkage errors (i.e. consumer or employee theft, shoplifting, administration and paperwork errors, vendor fraud), and inaccessible inventory (i.e. misplaced item) (Sarac et al., 2010) may affect both retailers and manufacturers of the same information sharing SC. In this case, it is expected that inventory errors across several members could even more exasperate the information distortion and propagate the bullwhip effect along the SC (Dai & Tseng, 2012, Xu et al., 2012). Despite the importance of this phenomenon, only a few papers have explored the impact of inaccurate information on the benefits of information sharing (Kwak & Gavierneri, 2014). Indeed, most related literature makes the aprioristic assumption that data used is highly accurate (Kapoor, 2009).

In this context, this paper wishes to contribute to this stream of literature by analysing the impact of the IRI on the dynamics of collaborative supply chains, both in terms of operational performance (i.e. order and inventory stability) and customer service level.

The rest of the paper is organized as follows. Section 2 explains the main motivations of our study and presents the problem statement and details the objective of our work. The modelling assumptions and the mathematical formalisms are presented in Section 3. Section 4 reports simulation experiments and discusses the performance metrics adopted in this work, i.e., bullwhip ratio, inventory variance ratio and backlog. Sections 5 and 6 provide discussions and managerial implications, respectively. Conclusions and suggestions for future research developments are presented in the last section.

2. Research motivation and problem statement

In the scientific literature, there are two main streams of research dealing with SC modelling and analysis under the assumption of IRI. The former has focused on the optimization of inventory policies in presence of errors (Sahin et al., 2009), while the latter on the impact of inventory data inaccuracies on the behaviour of SCs. The studies belonging to the first stream usually adopt OR techniques, mainly due to the fact that these techniques are very suitable at a local (i.e. single-node) tactical level in the design of SCs and in day-by-day decision making (Cannella & Ciancimino, 2010; Riddalls, Bennett, & Tipi, 2000). Thus, this approach is the most appropriate tool for solving problem such as the determination of the optimal order policy in presence of error (Sahin et al., 2009), or the required buffer size to minimize shortage costs for specific order rules (Thiel et al., 2010), among others.

On the contrary, studies in the second stream are commonly undertaken using methodologies based on the dynamics of system (i.e. system dynamics simulation, discrete event simulation, or agent-based simulation). These approaches are considered to be more suitable for studying the implications of the strategic design on SC performance and on the global behaviour of the network (Riddalls, Bennett, & Tipi, 2000, Cannella, Barbosa-Povoa, Framinan, & Relvas, 2013a, Dominguez & Framinan, 2013). Furthermore, the majority of these studies in this stream mainly focus on the impact of IRI on traditional SC structure. To the best of our knowledge, only few studies have analysed the effect of the IRI in collaborative SCs (see e.g. Fleisch & Tellkamp, 2005, Sari, 2008, Dai & Tseng, 2012). Although these works have certainly contributed to show how the whole performance of a specific SC structure can be affected by the discrepancy between the physical inventory and the information inventory, they have not addressed on the dynamic effect at the different stages of the SC. The only work that explicitly studies the effect of IRI in a collaborative SC (i.e. Sari, 2008) measures the total cost for the entire SC and the customer service level of the retailer. In addition, there are not quantitative studies showing how IRI impacts on customer service level in the upstream partners of a SC[1]. Nonetheless, in the presence of structured contracts between partners, if the retailer receives her orders after the due date, the supplier might be subject to a penalty (Eliman & Dodin, 2013). In fact, the cost of late-delivered and cancelled orders due to stock-outs is commonly observed in practice, and needs to be considered (Miranda & Garrido, 2009, Lu, Tsai, & Chen, 2012). Therefore, it can be concluded that the effect of IRI is not confined to the operational performance of the retailer but also impacts the performance of upstream SC partners (Xu et al., 2012, Dai & Tseng, 2012).

Motivated by these observations, the proposed research aims at contributing to the quantification of the impact of IRI on the operational performance and customer service level in collaborative SCs. More specifically, the objective is to analyse and contrast the effect of IRI on the different stages of a collaborative SC structure. To fulfil this research objective, we study and compare the response of the different echelons of the Information Exchange Supply Chain (IESC) (Holweg et al., 2005) in terms of demand amplification, inventory stability and customer service level of under two scenarios (1) accurate inventory record and (2) error in inventory record. In order to study the performance of the different echelons we adopt a classical four-serial multi-echelon structure (i.e. 1 Retailer, 1 Wholesaler, 1 Distributor and 1 Manufacturer) as in other several studies dealing with the dynamics of supply chains (see e.g. Sterman et al., 1989,

[1] The related literature rarely emphasizes the effect of inventory inaccuracy upon service-level quality (Thiel et al. 2010)

Dejonckeere et al., 2004, Chatfield, 2013). To make our findings more general, we assume that the replenishment in each stage of the structure is generated by adopting the periodic-review Order-Up-To (S, R) (Disney & Lambrecht, 2008, Ciancimino, Cannella, Bruccoleri, & Framinan, 2012), which is widely used in practical applications. In this policy, the system's inventory position (on-hand inventory + outstanding orders + backorders) is reviewed every period and an "order" is issued to bring the inventory position 'up-to' a defined level. To model inventory inaccuracy, we simulate a gap between the physical inventory, (i.e. the units actually available in stock) and the inventory record, (i.e. the units that, according to the information system, are available in stock). Thus, the periodic order generated by the SC's members is based on the level of inventory recorded by the information system and not on the level of actual current inventory. More specifically, we focus on an inventory inaccuracy condition caused by a specific error: the shrinkage error, a permanent inventory loss, resulting in smaller actual inventory when compared to the record in the Information Technology (IT) system (Dai & Tsang, 2012). It is to note that current inventory control systems do not take into account the disappearing inventory due to this shrinkage (DeHoratious & Raman, 2008). We focus on this particular type of inaccuracy for three reasons. Firstly, among all inventory inaccuracy sources, shrinkage has the biggest impact on SC costs (Beck, 2002, Fleisch & Tellkamp, 2005, Gumrukcu et al., 2008, Rekik, Sahin, & Dallery, 2009, Agrawal & Sharda, 2012, Dai & Tsang, 2012, Zhu, Mukhopadhyay, & Kurata, 2012, Kok & Shang, 2014). Secondly, the impact of inaccuracies due to different causes should be accounted for separately, since actions to address different causes may be quite different (Gel et al., 2010). Finally, the literature addressing IRI in general, and errors resulting from shrinkage in particular, is limited (Rekik & Sahin, 2012). In line with previous studies (Fleisch & Tellkamp, 2005, Sari, 2008, Dai & Tsang, 2012) the inaccuracy is modelled in each SC member.

As this study belongs to the stream of research on IRI dealing with the impact of inventory data inaccuracies on the behaviour of SCs, we adopt a methodology based on the dynamic of systems, i.e. the System Dynamics modelling approach (Forrester, 1961). This methodology has largely contributed to the development and improvement of operations management and nowadays continue to play a crucial role in advancing knowledge supply chain (see e.g., Sterman, 1989; Holweg & Bicheno, 2002, Akkermans & Dellaert, 2005, Croson & Donohue, 2006, Yuan et al., 2010, Cannella, Ciancimino, & Framinan, 2011, Syntetos, Georgantzas, Boylan, & Dangerfield, 2011, De Marco, Cagliano, Nervo, & Rafele, 2012, Hussain, Drakem, & Lee, 2012, Tako & Robinson, 2012, Campuzano-Bolarín, Mula, & Peidro, 2013, Hämäläinen, Luoma, & Saarinen, 2013, Mula, Campuzano-Bolarin, Díaz-Madroñero, & Carpio, 2013, Cannella, Bruccoleri, Barbosa-Povoa, & Relvas, 2013b, Spiegler & Naim, 2014). With this research we expect to show how the expected benefits in the IESC may be compromised by IRI, not only in terms of bullwhip effect and inventory variability, but also in terms of customer service. These results can help us to characterise the role of incentives that could be provided by the upstream echelons to the downstream echelons for limiting the detrimental consequence of "phantom inventory", preserving the benefits of SC collaboration.

3. Supply chain model

In IESC the information flow consists on the transmission of orders to upstream members and on sharing with them the information on market demand. An echelon i receives information on the order quantity from the downstream adjacent echelon and on the up-to-date market demand. This echelon then generates the order quantity on the basis of local data and parameters, incoming orders and market demand. Unlike traditional SC, all echelons receive information about market demand. The customer demand forecast is, indeed, directly included in the replenishment rule (Cannella & Ciancimino, 2010). Fig. 1 shows up the information flow in the Information Exchange SC.

The following assumptions characterise the SC model presented in this work:

(a) Single-product, K-stage production–distribution serial system. Each echelon in the system has a single successor and a single predecessor. The generic echelon's position is represented by index i. Echelon $i = 1$ stands for the manufacturer and $i = K + 1$ for the final customer.
(b) Non-negative condition of order quantity. Products delivered cannot be returned to the supplier.
(c) Backlogging is allowed as a consequence of stockholding. In each echelon the backlog will be fulfilled as soon as on-hand inventory becomes available. Therefore, orders not fulfilled in time are backlogged so that inventory remains a positive or null value.
(d) A generic echelon i receives information on the order quantity O_{i+1} from the downstream adjacent echelon and on the up-to-date market demand d.
(e) In order to simulate IRI, we consider two types of inventories: the physical inventory, i.e. actually available units, and the inventory record, i.e. what it is available according to the information system.
(f) According to Fleisch & Tellkamp (2005), in order to simulate the rational behaviour of the inventory manager and to isolate the effect of the inventory error on the SC performance, we do not consider a periodic inventory cycle counting. The alignment between the Physical Inventory and the inventory record is merely performed when a given low value of inventory is achieved.
(g) Inaccuracy condition is modelled for any SC member by inserting an error factor in each period's actual inventory position. More specifically, IRI is generated by modelling the shrinkage error (or stock loss error). We assume that, in each time period, the physical inventory is decreased by the Shrinkage Flow.
(h) The adopted replenishment rule is a periodic-review Order-Up-To (S, R) (Disney & Lambrecht, 2008). More specifically, we adopt a specific typology of Order-Up-To named Automatic Pipeline Variable Inventory and Order Based Production Control System (APVIOBPCS) (Dejonckheere, Disney, Lambrecht, & Towill, 2003, Lalwani, Disney, & Towill, 2006, Sarimveis, Patrinos, Tarantilis, & Kiranoudis, 2008, Cannella et al., 2011, Wang, Disney, & Wang, 2012).

The above assumptions are commonly adopted in supply chain dynamics literature, as it has been proved that the results obtained work for the real business worlds (see e.g. Sterman, 1989). Furthermore, thanks to these assumptions we can easily contrast the trend of the demand amplification with other analogous published works focusing on behaviour of collaborative supply chain. Among those Chatfield, Kim, Harrison, & Hayya (2004), Dejonckheere et al. (2004), Crespo Marquez (2010), Cannella & Ciancimino (2010), Barlas & Gunduz (2011), Ciancimino et al. (2012) can be mentioned.

The mathematical nomenclature is reported in Table 1.

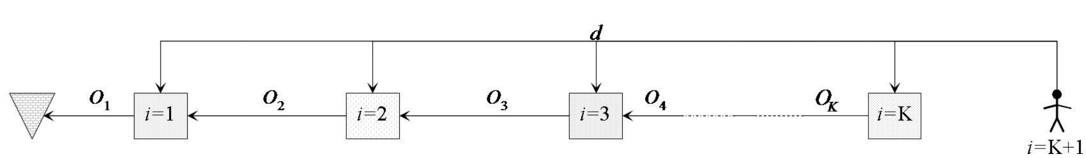

Fig. 1. The Information Exchange SC (source: Cannella & Ciancimino, 2010).

Table 1
Model nomenclature.

Variables			
B	Backlog	pI	Physical inventory
C	units/orders delivered	rI	Inventory record
d	Market demand	O	Replenishment order quantity
$\hat{d}$	Market demand forecast	TI	Target work in progress
Z	Inventory inaccuracy record	TW	Target inventory
Sf	Shrinkage flow	W	Work in progress
Parameters			
α	Forecast smoothing factor	T	Time horizon
λ	Shrinkage error	Tc	Safety stock factor
ψ	Inventory alignment boundary	Tp	Production-distribution lead time
i	Echelon's position in the SC	Tw	Work in progress proportional controller
K	Total number of echelons	Ty	Inventory proportional controller
Statistics			
σ_d^2	Variance of the market demand	σ_O^2	Variance of the order quantity
σ_I^2	Variance of the inventory	μ_d	Steady state market demand

Table 2
Equation system.

Order quantity	$O_i(t) = \hat{d}_K(t) + \frac{1}{Tw_i}(TW_i(t) - W_i(t)) + \frac{1}{Ty_i}(TI_i(t) - rI_i(t))$	(1)
Physical inventory	$pI_i(t) = pI_i(t-1) - Sf_i(t) + C_{i-1}(t - Tp_i) - C_i(t)$	(2)
Inventory inaccuracy	$Z_i(t) = \begin{cases} Z_i(t-1) + Sf_i(t) & pI_i(t) > \psi \\ 0 & pI_i(t) \le \psi \end{cases}$	(3)
Inventory record	$rI_i(t) = pI_i(t-1) + Z_i(t)$	(4)
Target work in progress	$TW_i(t) = Tp_i\hat{d}_i(t)$	(5)
Target inventory	$TI_i(t) = Tc_i\hat{d}_i(t)$	(6)
Work in progress	$W_i(t) = W_i(t-1) + C_{i-1}(t) - C_{i-1}(t - Tp_i)$	(7)
Shrinkage flow	$SF_i(t) = pI_i(t-1) * \lambda_i$	(8)
Backlog	$B_i(t) = B_i(t-1) + O_{i+1}(t) - C_i(t)$	(9)
Orders delivered	$C_i(t) = \min\{O_{i+1}(t) + B_i(t-1); pI_i(t-1) + C_i(t - Tp_i)\}$	(10)
Demand forecast	$\hat{d}_i(t) = \alpha O_{i+1}(t-1) + (1-\alpha)\hat{d}_i(t-1)$	(11)
	$O_{K+1}(t) = d(t)$	(12)
Non-negativity condition of order quantity	$O_i(t) \ge 0$	(13)
Uncapacitated raw material supply condition	$C_{i-1}(t) = O_1(t);\ i = 1$	(14)

The mathematical model of the SC configurations is reported in Table 2. The replenishment order quantity (Eq. (1)) is the sum of the following components: market demand forecast (Eqs. (11) and (12)), work in progress gap, and inventory record gap. The work in progress gap is the difference between target work in progress (Eq. (5)) and the work in progress (Eq. (7)). The relation regulating the work in progress variable is such that, for each echelon i, the products sent from supplier $C_{i-1}(t)$ immediately become work in progress. Thus, for a generic echelon i at time t, work in progress is increased by quantity $C_{i-1}(t)$ (items sent by the supplier $i-1$ at time t) and decreased by quantity $C_{i-1}(t - Tp_i)$ (items sent by the supplier $i-1$ at time $t - Tp$). The target work in progress is the product of the forecast on the order from the subsequent echelon and the production-distribution lead time (Eq. (5)). This gap is divided by the work in progress proportional controller.

The inventory record gap is the difference between target inventory (Eq. (6)) and inventory record, divided by the inventory proportional controller. The target inventory (Eq. (6)) is the product of the forecast on the order from the subsequent echelon and the safety stock factor. According to assumption (f), inventory record (Eq. (4)) is equal to physical inventory increased by the shrinkage flow (Eq. (8)), if the physical inventory (Eq. (2)) is greater than a perceptual of the physical inventory at the initial time simulation (Eq. (3)). Analogously, if the physical inventory is lower than this percentage, the recorded inventory matches the physical inventory and the real level of inventory on-hand is used in the order policy. The physical inventory (Eq. (2)) every review time is increased by the quantity $C_{i-1}(t - Tp_i)$ (items sent by supplier $i-1$ at time $t - Tp$), decreased by the quantity $C_i(t)$ (items sent to the downstream echelon) and by the shrinkage flow (Eq. (8)). According to assumption (g), this flow is equal to the physical inventory level at the previous time period multiplied by the shrinkage error value λ. The dynamic of the discrepancy between the physical inventory level and the inventory record level is regulated by Eq. (3).

Eq. (9) describes the backlog as the sum of unfulfilled orders (orders from the subsequent echelon minus delivered items). Eq. (10)

defines the item delivery from one echelon to its successor. Eq. (11) models the exponential smoothing demand forecast rule, where the value of α reflects the weight given to the most recent observation. Eq. (12) defines that the order received in echelon K (retailer) is equal to the customer demand. Eq. (13) models the non-negativity condition of order quantity. Eq. (14) models the unlimited raw material availability assumption, i.e. orders from echelon $i = 1$ are always entirely fulfilled.

4. Experimental design and results

To set the numerical values for the experiments, we employ values taken from the related literature. More specifically, lead time values, the demand smoothing forecasting factor, and the safety stock factor refer to the setting of the beer game model by Sterman (1989). This setting was used in several relevant SC analyses, such as Wikner, Towill, & Naim (1991), Van Ackere, Larsen, & Morecroft (1993), Machuca & Barajas (2004), Strozzi, Bosh, & Zaldivar (2007), Jakšič & Rusjan (2008), Wright & Yuan (2008), Crespo Márquez (2010), Barlas & Gunduz (2011), or Ciancimino et al. (2012), to name a few.

The customer demand is modelled according to the framework proposed by Towill, Zhou, & Disney (2007) for studying the bullwhip effect. This framework suggests the typology of endogenous input that can be adopted in bullwhip analysis in order to study different characteristics of the SC (Domínguez, Framinan, & Cannella, 2014). In our experiment we adopt the so-called "variance lens perspective", by which we infer on the performance of SC under stable market condition emulated by a stationary input demand.

The numerical experiments are performed under the following settings:

- The serial system is composed by four echelons ($K = 4$), i.e. Retailer ($i = 4$), Wholesaler ($i = 3$), Distributor ($i = 2$), and Manufacturer ($i = 1$).
- Inventory alignment boundary is $\psi = 0.1 * I_i(0)\,\forall i$.
- The levels of the proportional controller is $T_y = T_w = 2T_p$.
- The customer demand is: $N(\hat{i}_d, \acute{o}_d) = N(100, 10)$.
- The initial values of the state variables are: $[W_i(0), I_i(0), B_i(0)] = [T_p d(0), T_c d(0), 0]\forall i$.
- The lead time levels is $T_p = 2\,\forall i$.
- The safety stock factor is $T_c = 3\,\forall i$ [2].
- The demand smoothing forecasting factor is $\alpha = 0.33\,\forall i$.
- Numerical experiments are performed for a time length $T = 1000$.
- The solutions for the initial-value problem are approximated through Vensim PLE.

We conducted four sets of experiments under four levels of shrinkage errors: [$\lambda^1 = 0$ percent; $\lambda^2 = 1.5$ percent; $\lambda^3 = 3.0$ percent; $\lambda^4 = 4.5$ percent] $\forall i$. Percentages of four levels have been chosen from the work of Raman, DeHoratius, & Ton (2001). Based on these studies, an average inaccuracy level of 3 percent of the physical inventory is adopted. Since, according to Fleisch & Tellkamp (2005), there are no sources providing comparable data for distributors and producers, we use the same data for all echelons.

For each set of experiments, we conducted 30 replications in order to guarantee, for the output variables, that the width of the 95 percent confidence intervals of the mean is lower than 10 percent of the mean itself. This value has been computed with GPower 3 Statistical software.

The SC operational performance was measured via a set of metrics whose reduction reflects the improvement in cost effectiveness of members' operations (Cannella et al., 2013a). Such metrics are the bullwhip ratio (Eq. (15)) proposed by Chen, Drezner, Ryan, & Simchi-Levi (2000) and the inventory variance ratio (Eq. (16)), proposed by Disney & Towill (2003). On the contrary, mean backlog (Eq. (17)) is representative of customer service level. This metric is derived by the backlog (Eq. (6)), which represents a cumulative measure of undelivered goods to the final customer. The magnitude of this metric shows how a generic echelon is able to fulfil customer (internal customer or consumer) orders.

$$\textit{Bullwhip ratio}_i = \frac{\sigma^2_{O_i}/\mu_{O_i}}{\sigma^2_d/\mu_d}\,, \tag{15}$$

$$\textit{Inventory variance ratio}_i = \frac{\sigma^2_{I_i}/\mu_{I_i}}{\sigma^2_d/\mu_d}\,, \tag{16}$$

$$\textit{Mean backlog}_i = \frac{1}{T}\sum_{t=0}^{T} B_i \tag{17}$$

This bullwhip ratio provides information on potential unnecessary costs for suppliers, such as lost capacity, or opportunity costs and overtime working and subcontracting costs (Cannella et al., 2013a). The inventory variance ratio quantifies the fluctuations in inventory. An increased inventory variance results in higher holding and backlog costs, inflated average inventory cost per period (Disney & Lambrecht, 2008), and increasing holding costs per unit, missing production schedules, job sequencing and resource re-allocation. Finally, the backlog is a cumulative measure of undelivered goods to the final customer and is recorded to assess customer service level.

Results from the ANOVA, conducted using the Minitab software tool, are reported in Table 3. Columns report the performance parameters, the F values (the statistic used to test that the effects of λ factor are significant), and the p-values (Montgomery, 2005).

In Table 4, the values for the bullwhip ratio and Inventory variance ratio are presented. Results are reported by echelon (column), and by shrinkage error levels (row).

Finally Table 5 reports the average backlog and the maximum backlog for each echelon. Analogously to Table 4, results are reported by echelon (column), and by shrinkage error levels (row).

5. Discussion

This section is devoted to a technical comment on the output presented in the previous one. In general, we observe that the error destroys the benefits provided by the adoption of collaboration practices in SC. The main results of the work are presented in the following subsections.

5.1. The value of accurate information in collaborative supply chain

In order to analyze the impact of the error in the different echelons of the chain, we first consider the benchmark scenario, i.e. the set characterized by the absence of inventory inaccuracy error (λ^1) (Table 4). As expected, the Information Exchange SC, under the assumption of accuracy in data inventory, is able to limit the propagation of the bullwhip effect and of inventory instability phenomenon. Unlike the traditional SC structure, where a node-to-node 1:20 increase in bullwhip effect is observed (Geary, Disney, & Towill, 2006), in our experiment the average increases is no higher than 1:2 for the bullwhip ratio, and 1:2 for the inventory variance ratio. In our experiment, as in Chatfield et al. (2004) and Dejonckheere (2004), Information Exchange SC exhibits a merely linear increase of order variance in up-stream direction (Cannella & Ciancimino, 2010), in contrast to the exponential increase presented in the traditional SC (Disney et al., 2004). This result confirms several empirical studies of

[2] As the stock-out phenomenon due to the variability of the market demand can contribute to the generation of bullwhip effect, in order to isolate the effect of the IRI on the dynamic behaviour of the supply chain, the safety stock factor is overestimated (i.e. three times the value of the mean demand).

Table 3
ANOVA outputs.

Performance parameters	*F*-Fisher	*P*-value	Performance parameters	*F*-Fisher	*P*-value
$ORVrR_4$	270.63	0.000	$IVrR_4$	1674.27	0.000
$ORVrR_3$	194.17	0.000	$IVrR_3$	334.52	0.000
$ORVrR_2$	330.91	0.000	$IVrR_2$	361.22	0.000
$ORVrR_1$	486.33	0.000	$IVrR_1$	427.94	0.000
MB_4	-	-	$MaxBL_4$	-	-
MB_3	65.69	0.000	$MaxBL_3$	121.64	0.000
MB_2	214.12	0.000	$MaxBL_2$	238.12	0.000
MB_1	222.29	0.000	$MaxBL_1$	386.43	0.000

Table 4
Bullwhip ratio and inventory variance ratio.

		Order rate variance ratio				Inventory variance ratio			
		$i = 4$	$i = 3$	$i = 2$	$i = 1$	$i = 4$	$i = 3$	$i = 2$	$i = 1$
$rI_i(t) = pI_i(t)$	λ^1	0.335	0.490	0.890	1.68	0.370	0.770	1.56	3.11
$rI_i(t) \neq pI_i(t)$	λ^2	4.429	17.92	42.57	64.91	144.55	190.60	268.40	332.89
	λ^3	8.890	36.95	86.04	124.66	148.04	255.98	411.91	472.20
	λ^4	12.651	59.81	136.01	186.25	149.89	320.55	519.98	547.54

Table 5
Average backlog and max backlog.

		Average backlog				Max backlog			
		$i = 4$	$i = 3$	$i = 2$	$i = 1$	$i = 4$	$i = 3$	$i = 2$	$i = 1$
$rI_i(t) = pI_i(t)$	λ^1	–	–	–	–	–	–	–	–
$rI_i(t) \neq pI_i(t)$	λ^2	–	2.707	7.746	9.920	–	195.88	464.8	455.90
	λ^3	–	6.369	19.123	24.390	–	353.36	686.2	597.57
	λ^4	–	10.268	33.783	48.492	–	366.96	718.8	611.60

Holweg et al. (2005) and theoretical studies on the benefits provided by the information sharing in terms of bullwhip reduction.

5.2. The impact of level of IRI in the propagation of the demand amplification phenomenon: as the level of the error increase the bullwhip effect and inventory stability monotonously increase and customer service level decrease

Now we focus on the experiments characterized by the shrinkage error. First of all, ANOVA results reveal that the inventory error is a significant factor for each echelon and for all performance measures (Table 3). Then, by comparing these scenarios with the Information Exchange SC under precise inventory information, a relevant difference for all members in the SC can be noted in terms of order and inventory stability, as well as in customer service level. The bullwhip in Echelon $i = 1$ (Manufacturer) increases from 1.68 to 186.25 when shifting from the inventory accuracy scenario ($\lambda^1 = 0$ percent) to the inventory inaccuracy scenario with the highest shrinkage error ($\lambda^4 = 4.5$ percent). Similarly, its inventory variance increases from 3.11 to 547.45 (see Table 4). Analogously, customer service level suffers from a violent perish. Unlike the benchmark experiment, where the mean backlog at each level of the chain is equal to zero (i.e. 100 percent customer service level), the scenarios characterized by the shrinkage error reveal an intensive increasing of backlog.

This result shows how the presence of errors destroys the bullwhip avoidance feature of the collaboration. This performance decline occurs at each stage of the chain affected by the IRI. However, it is worth to note that the magnitude of the decline both for operational metric and customer service level is different for different values of the error. In fact, as we move from retailer to supplier, orders and inventories variability and stock-out events increase as the level of error increases. Essentially, not only the presence of error impacts on the deterioration of the performance, but also its magnitude represents a key factor in the deterioration of the dynamic behaviour of the SC.

5.3. The detrimental impact of small level of IRI: even low values of error can destroy the bullwhip avoidance feature of collaboration in supply chain

As previously discussed, SC performance decreases as the magnitude of the error increases. However, the magnitude of this trend noticeably decreases with respect to the benchmark scenario (zero error). If we analyze the values of bullwhip ratio by columns, results reveal on average a 1:38, a 1:76 and a 1:116 increment in bullwhip magnitude by shifting from λ^1 to λ^2, λ^3, and λ^4 respectively (see Table 4). On the contrary, when shifting from $\lambda^2 = 1.5$ percent to $\lambda^3 = 3.0$ percent, results show on average a 1:2 increment in the bullwhip ratio at each stage of the chain (see Table 4). Analogously, when shifting from $\lambda^3 = 3.0$ percent to $\lambda^4 = 4.5$ percent, we note on average a 1:1.5 increment of the bullwhip ratio.

This result shows how even a relative small value of inventory error may lead to a notable deterioration in SC performance and to the generation of significant unnecessary costs. This finding is particularly relevant because it points out that reducing (not avoiding) IRI could not entail the wished benefits of SC collaboration.

5.4. The different impact of IRI on lower stages and higher stage of the supply chain: as the level of error increase the unnecessary costs experimented by the higher stage are superior to the same costs for the lower stages

By analysing the values of inventory variance ratio and bullwhip ratio, we can note the similar trend of the two performance metrics as we move from retailer to manufacturer, regardless by the error level. As previously analysed, there is basically a monotonic increase in demand amplification and in inventory instability as the level of error increases. However, by focusing on the retailer stage we note how the inventory variance ratio reveals a different response to the variation of the inventory error. In fact, it shows a 3.7 percent increase when moving from $\lambda^1 = 1.5$ percent to $\lambda^4 = 4.5$ percent. On the contrary, as the shrinkage error increases, the upstream stages are characterized by sensible deterioration in inventory variance ratio, presenting the similar trend exposed in terms of bullwhip ratio. Particularly, echelon $i = 1$ (Manufacturer) shows a 63.9 percent increase when moving from $\lambda^1 = 1.5$ percent to $\lambda^4 = 4.5$ percent (see Table 4).

This result shows two further findings. Firstly we note how, if the collaborative SC structure is affected by the inventory error, the upstream stages are the members of the structure that suffer most the detrimental consequences of the bullwhip effect, regardless the magnitude of the error. Thus, they will experiment higher holding costs, missing production schedules, job sequencing and resource re-allocation costs than the downstream stage. Secondly, the upstream stages are more affected by the magnitude of the error with respect to the downstream stages, particularly in terms of inventory holding costs. It seems thus reasonable to consider that this sensitivity to the magnitude of the error is due not only by the mere IRI problem in their own stages, but also from the propagation of the IRI damaging effect to the downstream stages

5.5. The customer service is affected by IRI at upper stages of the supply chain: as the level of error increase the stock out phenomenon increase

Finally, we focus on the backlog in order to evaluate the effect of the error in terms of customer service level. In general, similarly to the operational performance, the SC reveals a monotonic deterioration of the customer service level by shifting from the benchmark experiment to the inventory inaccuracy scenarios. More specifically, the results show that the upstream stages of the SC significantly suffer from IRI, and they are particularly sensitive to the magnitude of the shrinkage error (Table 5). In fact, echelon $i = 1$ (Manufacturer) presents a 1:5 increase in mean backlog by shifting from low error design ($\lambda^1 = 1.5$ percent) to the highest shrinkage error design ($\lambda^4 = 4.5$ percent) (see Table 3), unlike the deterioration of the operational metrics where the same echelon shows an increase less than 1:3 for the bullwhip ratio and less than 1:2 for the inventory variance ratio (see Table 4). Even for this metric, the Manufacturer is the member whose performance is more affected by the inventory error.

6. Implications

The findings of this work reveal some interesting insights concerning the impact of the IRI in a collaborative SC. The main results of the work are presented in the following sections.

6.1. Undermining the benefits of this investment in IT

The most relevant finding is that the inventory inaccuracy, in this case the shrinkage error, may nullify the benefits provided by the IESC. This SC structure largely advocated for its bullwhip dampening, inventory stabilizing, and total cost reducing effects (see e.g. Machuca & Barajar, 2004, Disney et al., 2004, Dejonckheere et al., 2004, Holweg et al., 2005, Agrawal et al., 2009, Cannella & Ciancimino, 2010, Yuan et al., 2010, Ali & Boylan, 2011, Ali et al., 2012, Trapero et al., 2012), is not able to avoid the detrimental phenomenon of demand amplification when the members of the SC are affected by the inventory inaccuracy problem. From a managerial point of view, this negative impact represents a no-trial dilemma. In fact, in the real business world, implementing an Information Exchange SC means adopting a large-scale collaboration project. This kind of solution imposes its own logic on a company's strategy, organization and culture (Cannella & Ciancimino, 2010). Developing an information-sharing culture as an organizing context is not easy (Fawcett, Wallin, Allred, Fawcett, & Magnan, 2011) and implementing collaboration practices requires large investments of money, time, and expertise (Davenport, 1998, Cannella & Ciancimino, 2010, Cannella, Ashayeri, Miranda, & Bruccoleri, 2014, Wiengarten, Humphreys, McKittrick, & Fynes, 2013). IT is certainly an enabler for SC members to share information quickly, accurately and inexpensively (but not at zero costs) (Chan & Chan, 2010). Our results show how IRI can undermine the benefits of this investment in IT. Furthermore, it is reasonable to assert that the detrimental consequences of the bullwhip effect are even more drastic. In fact, the members of the SC suffer from the classical unnecessary costs of the demand amplification phenomenon presented in the traditional SC, i.e. lost capacity or opportunity costs and overtime working and subcontracting costs, higher production/transportation set-up costs, scheduling and resource re-allocation costs as well as slack and extra-capacity of distribution system costs, etc. This structure is by nature extremely prone to bullwhip effect (Disney et al., 2004) mainly due to the lack of visibility on the customer demand. On the contrary, in the Information Exchange SC under the IRI the root cause of these unnecessary costs is the so-called "phantom inventory" (Hardgrave et al., 2013). The incapability of capturing the timely shrinkage information is the key driver for the detrimental consequences of the bullwhip effect (Dai & Tzang, 2012). However, unlike in the traditional SC, in this collaborative structure, the partners have previously invested in a costly strategy aimed at avoiding these mentioned unnecessary costs. For this reason, we consider that the costs of information distortion in collaborative SCs can be even more exacerbated as compared to those in the traditional structure. This problem shed some light to the frustration experimented by some SC managers with the lack of financial return on SC collaboration effort (Holweg et al., 2005).

6.2. Sharing benefits for zero inventory error policy

The standard way to reduce the IRI problem is by accomplishing costly audits (de Kok, van Donselaar, & van Woensel, 2008; Kok & Shang, 2014). In general, low inventory audit frequencies are only partially effective in controlling the economic impact of record inaccuracies. The effectiveness of inventory audits increases as more and more audits are performed. However, one should recognize that inventory audits, such as cycle counting, are expensive and disruptive (Gel et al., 2010). Furthermore, our analysis shows that even small inventory inaccuracy leads a violent deterioration of the performance not only in terms of bullwhip effect and inventory variability, but also in terms of customer service level. Thus, even the inventory audit cannot be always able to solve this problem.

In this context, this study suggests that the way to decrease or remove a considerable amount of inaccuracies is to adopt a conjoint approach of "prevention" and "integration". The former aims at eliminating the root causes of IRI through the implementation and execution of process improvement. The latter is based on the design of inventory planning and decision tools robust enough to account for the presence of record inaccuracy (Dehoratius, Mersereau, & Schrage, 2008).

In particular, our results suggest that this approach should be firstly promoted by the upstream stages, i.e. the Manufacturer. In fact, they are the members of the chain who suffer more from inventory inaccuracy both in terms of bullwhip effect and inventory instability, and out-of-stock. Thus, the upstream stages do not only face the extra costs due to the demand amplification, but also the risk of paying penalties to their direct customers for a problem generated by the customers themselves.

In this context, the conjoint approach of prevention and integration can be realized by adopting strategies based on the "sharing of benefit" among partners (Audy, Lehoux, D'Amours, & Rönnqvist, 2012, Chan, Choi, & Hui, 2012). In collaborative SCs, one of the main barriers to real collaboration is the reluctance of the companies to share operational information regarding their own core business (Cannella & Ciancimino, 2010). It has been shown that information sharing can hurt retailers' interests, and thus the retailers are discouraged from sharing their demand information with the manufacturer. In order to obtain this strategic information, manufacturer tends to reward retailers (Qian, Chen, Miao, & Zhang, 2012). On the other hand, in a recent work, Chan et al. (2012) propose a "surplus sharing contract" among partners and illustrated how a health care organization can achieve a win–win situation in which both supplier and healthcare organization can have improvements (in costs or profits) by avoiding the transaction error via a change in the scanning system. Similarly, concerning the shrinkage error, an analogous strategy could be developed, such as incentives for shrinkage error elimination through prevention and integration. This typology of error can be substantially avoided using RFID technology (Rekik, Sahin, Jemai, & Dallery, 2007) as items are continuously monitored. However, a recent study by Eurostat (the statistical office of the EU) published in their newsletter showed that only 3 percent of the EU companies use RFID technology (Zhu et al., 2012). In this context, the upstream stages should encourage their direct customers to adopt this technology even for the detection of the inventory error. In other words, in collaborative SC systems, the upstream stages not only should reward retailers in order to obtain precise information about the customer demand, but also, should promote and implement strategies analogous to the one proposed by Chan et al. (2012) for realising a "zero inventory error policy" and avoiding the risk of nullifying the investment in information technologies. When implementing SC collaboration strategies, managers should make IRI-related decisions in order to ensure the effectiveness of such collaboration.

7. Conclusions

The aim of this paper is to analyse the impact of the IRI on a collaborative SC structure, i.e. the IESC. Inaccuracy was modelled for any SC member by inserting an error factor in each period's actual inventory position. More specifically, IRI was generated by modelling the shrinkage error (or stock loss error). We have compared the performance of this collaborative SC under perfect inventory record information with the behavioural response under the presence of the inventory error. SC performance has been measured in terms of the bullwhip ratio and the inventory variance ratio in order to assess the dynamics of the system's response in terms of bullwhip effect and inventory stability, and with the mean backlog for assessing the customer service level at each level of the SC.

The simulation results have shown how the benefits provided by sharing information by SC members are strongly compromised by the inaccuracy in the inventory recording activity. More specifically, there is an intense deterioration on the performance of the SC for the upstream stages of the chain. This indicates how IRI can undermine the benefits of the investments in connectivity technologies. Furthermore, due to the fact that the detrimental effect of inaccuracy in upstream SC partners is higher than in downstream partners, the upstream stages – i.e. the manufacturer – not only potentially experiment the extra costs due to the demand amplification, but are also subject to the risk of paying penalties to their direct customers … for a problem generated by the customers themselves! Also, our results show that, no matter what the magnitude of the error is, its effect on performance is dramatic. Thus, we can argue that, in order to benefit from the advocated bullwhip avoidance property of the collaborative effort in SCs, the upstream member should promote strategies aimed at realising a "zero inventory error", such as prevention and integration policies. In this manner, we suggest to adopt the principle of "sharing of benefit" in SC. This action can represent a specific solution to avoid the risk of annihilating investments in SC collaboration effort and to guarantee a win–win situation among partners.

Unlike the few previous works dealing with the impact of the IRI in collaborative SC, this study focuses on dynamic responses at the different stages of the SC. Thus we have been able to specify the effect of IRI in any level of the SCs structures and to identify the members who are more affected by this problem. In this fashion, we have identified who should promote the improvement strategies for avoiding this phenomenon, and proposed how these strategies can be specifically implemented.

The limitations of the present study also represent opportunities for further research in this field. First, our research focus was set particularly on the impact of shrinkage error. In contrast, other sources of inaccuracies (e.g., misplacement, unreliable suppliers, transaction errors,) were not considered in our analysis. Further works can extend our model to include all such errors. In this work we have assumed the same inventory error for all echelons. Further models can consider different level of inventory error and focus on the relation between the different magnitude of the IRI and supply chain performance. Furthermore, we merely considered the no periodic inventory alignment condition. In our next step we want to extend this model to the periodic alignment policy in order to evaluate the trade-off between improving the accuracy of system reported inventory and the associated costs. In addition, our analysis is limited to a single product. Thus, it is not clear to what extent we may generalize from this results to multi-product SC. Also further studies can analyse and contrast the performance of different members of both traditional SCs and other enriched SCs (i.e. Synchronised SC) under the errors in inventory information. In addition, due to the increasing interest in sustainability issue in operations management, the impact of IRI on closed loop supply chain (Turrisi, Bruccoleri, & Cannella, 2013) can represent a significant new direction in supply chain dynamics studies. An additional effort can be represented by modelling IRI for different typologies of demand. Particularly, due to the extreme volatility and impetuous alteration of the market produced by the current economic recession (Cannella, Barbosa-Povoa, & Framinan, 2014), it can be relevant to analyse the response of a supply chain affected by IRI under stress impulse of the market demand. Finally, it has to be mentioned that this study has been developed adopting the serial SC assumption. Due to the increasing interest in the analysis of more complex supply chain (Dominguez et al., 2014), in future work we plan to study the effect of IRI on divergent SCs.

Acknowledgements

We wish to thank the anonymous referees for insightful comments on earlier versions of the paper. This research was supported by the European Commission/Andalusian Agency of Knowledge (Talentia Marie Curie Cofund Fellow) and by the Chilean National Science and Technology Research Fund (#11140593).

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.

Agrawal, P. M., & Sharda, R. (2012). Impact of frequency of alignment of physical and information system inventories on out of stocks: A simulation study. *International Journal of Production Economics*, *136*(1), 45–55.

Ali, M. M., Boylan, J. E., & Syntetos, A. A. (2012). Forecast errors and inventory performance under forecast information sharing. *International Journal of Forecasting*, *28*(4), 830–841.

Ali, M. M., & Boylan, J. E. (2011). Feasibility principles for downstream demand inference in supply chains. *Journal of the Operational Research Society*, *62*(3), 474–482.

Akkermans, H., & Dellaert, N. (2005). The rediscovery of industrial dynamics: The contribution of system dynamics to supply chain management in a dynamic and fragmented world. *System Dynamics Review*, *21*(3), 173–186.

Audy, J. -F., Lehoux, N., D'Amours, S., & Rönnqvist, M. (2012). A framework for an efficient implementation of logistics collaborations. *International Transactions in Operational Research*, *19*(5), 633–657.

Bai, L., Alexopoulos, C., Ferguson, M. E., & Tsui, K. -L. (2012). A simple and robust batch-ordering inventory policy under incomplete demand knowledge. *Computers and Industrial Engineering*, *63*(1), 343–353.

Barlas, Y., & Gunduz, B. (2011). Demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply chains. *Journal of the Operational Research Society*, *62*(3), 458–473.

Beck, A., 2002. Automatic product identification & shrinkage: Scoping the potential. ECR Europe.

Bruccoleri, M., Cannella, S., & La Porta, G. (2014). Inventory record inaccuracy in supply chains: The role of workers' behavior. *International Journal of Physical Distribution & Logistics Management*, *44*(10), 796–819.
Campuzano-Bolarín, F., Mula, J., & Peidro, D. (2013). An extension to fuzzy estimations and system dynamics for improving supply chains. *International Journal of Production Research*, *51*(10), 3156–3166.
Cannella, S., & Ciancimino, E. (2010). On the bullwhip avoidance phase: Supply chain collaboration and order smoothing. *International Journal of Production Research*, *49*(23), 7085–7105.
Cannella, S., Ciancimino, E., & Framinan, J. M. (2011). Inventory policies and information sharing in multi-echelon supply chains. *Production Planning & Control*, *22*(7), 649–659.
Cannella, S., Barbosa-Povoa, A. P., & Framinan, J. M. (2014). An IT-enabled supply chain model: A simulation study. *International Journal of Systems Science*, *45*(4), 2327–2341.
Cannella, S., Barbosa-Povoa, A. P., Framinan, J. M., & Relvas, S. (2013). Metrics for bullwhip effect analysis. *Journal of the Operational Research Society*, *64*, 1–16.
Cannella, S., Bruccoleri, M., Barbosa-Povoa, A., & Relvas, S. (2013). Methodological approach to studying the dynamics of production networks: A discrete event simulation model. *International Journal of Logistics Systems and Management*, *16*(2), 211–223.
Cannella, S., Ashayeri, J., Miranda, P. A., & Bruccoleri, M. (2014). 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. (2014). Order-up-to policies in information exchange supply chains. *Applied Mathematical Modelling*, *38*(23), 5553–5561.
Chan, H. -L., Choi, T. -M., & Hui, C. -L. (2012). RFID versus bar-coding systems: Transactions errors in health care apparel inventory control. *Decision Support Systems*, *54*(1), 803–811.
Chan, H. K., & Chan, F. T. S. (2010). A review of coordination studies in the context of supply chain dynamics. *International Journal of Production Research*, *48*(10), 2793–2819.
Chatfield, D. C., Kim, J. G., Harrison, T. P., & Hayya, J. C. (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. (2013). Underestimating the bullwhip effect: A simulation study of the decomposability assumption. *International Journal of Production Research*, *51*(1), 230–244.
Chen, F., Drezner, Z., Ryan, J., & 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.
Ciancimino, E., Cannella, S., Bruccoleri, M., & Framinan, J. M. (2012). On the bullwhip avoidance phase: The synchronised supply. *European Journal of Operational Research*, *221*(1), 49–63.
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. (2006). Behavioral causes of the bullwhip effect and the observed value of inventory information. *Management Science*, *52*(3), 323–336.
Dai, H., & Tseng, M. M. (2012). The impacts of RFID implementation on reducing inventory inaccuracy in a multi-stage supply chain. *International Journal of Production Economics*, *139*(2), 634–641.
Davenport, T. H. (1998). Putting the enterprise into the enterprise system. *Harvard Business Review*, *76*(4), 121–131.
De Marco, A., Cagliano, A. C., Nervo, M. L., & Rafele, C. (2012). Using system dynamics to assess the impact of RFID technology on retail operations. *International Journal of Production Economics*, *135*(1), 333–344.
de Kok, A. G., van Donselaar, K. H., & van Woensel, T. (2008). A break-even analysis of RFID technology for inventory sensitive to shrinkage. *International Journal of Production Economics*, *112*(2), 521–531.
Dehoratius, N., Mersereau, A. J., & Schrage, L. (2008). Retail inventory management when records are inaccurate. *Manufacturing and Service Operations Management*, *10*(2), 257–277.
DeHoratius, N., & Raman, A. (2008). Inventory record inaccuracy: An empirical analysis. *Management Science*, *54*(4), 627–641.
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., & Towill, D. (2003). On the bullwhip and inventory variance produced by an ordering policy. *Omega*, *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. R. (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.
Domínguez, R., & Framinan, J. M. (2013). A decision management tool: Modelling the order fulfilment process by multi-agent systems. *International Journal of Management and Decision Making*, *12*(3), 240–258.
Domínguez, R., Framinan, J. M., & Cannella, S. (2014). Serial versus divergent supply chain networks: A comparative analysis of the bullwhip effect. *International Journal of Production Research*, *52*(7), 2194–2210.
Eliman, A. A., & Dodin, B. (2013). Project scheduling in optimizing integrated supply chain operations. *European Journal of Operational Research*, *224*(3), 530–541.
Fawcett, S. E., Osterhaus, P., Magnan, G. M., Brau, J. C., & McCarter, M. W. (2007). Information sharing and supply chain performance: The role of connectivity and willingness. *Supply Chain Management*, *12*(5), 358–368.
Fawcett, S. E., Wallin, C., Allred, C., Fawcett, A. M., & Magnan, G. M. (2011). Information technology as an enabler of supply chain collaboration: A dynamic-capabilities perspective. *Journal of Supply Chain Management*, *47*(1), 38–59.
Fleisch, E., & Tellkamp, C. (2005). Inventory inaccuracy and supply chain performance: A simulation study of a retail supply chain. *International Journal of Production Economics*, *95*(3), 373–385.
Forrester, J. (1961). Industrial Dynamics. Cambridge: MIT Press.
Geary, S., Disney, S. M., & Towill, D. R. (2006). On bullwhip in supply chains – Historical review, present practice and expected future impact. *International Journal of Production Economics*, *101*(1), 2–18.
Gel, E. S., Erkip, N., & Thulaseedas, A. (2010). Analysis of simple inventory control systems with execution errors: Economic impact under correction opportunities. *International Journal of Production Economics*, *125*(1), 153–166.
Gumrukcu, S., Rossetti, M. D., & Buyurgan, N. (2008). Quantifying the costs of cycle counting in a two-echelon supply chain with multiple items. *International Journal of Production Economics*, *116*(2), 263–274.
Hämäläinen, R. P., Luoma, J., & Saarinen, E. (2013). On the importance of behavioral operational research: The case of understanding and communicating about dynamic systems. *European Journal of Operational Research*, *228*(3), 623–634.
Hardgrave, B. C., Aloysius, J. A., & Goyal, S. (2013). RFID-enabled visibility and retail inventory record inaccuracy: Experiments in the field. *Production and Operations Management*, *22*(4), 843–856.
Heese, H. S. (2007). Inventory record inaccuracy, double marginalization, and RFID adoption. *Production and Operations Management*, *16*(5), 542–553.
Hollinger, R.C., Adams, A. 2010. *2009 National Retail Security Survey Final Report*. Report, University of Florida, USA.
Holweg, M., & Bicheno, J. (2002). Supply chain simulation – A tool for education, enhancement and endeavour. *International Journal of Production Economics*, *78*(2), 163–175.
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.
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.
Jakšič, M., & Rusjan, B. (2008). The effect of replenishment policies on the bullwhip effect: A transfer function approach. *European Journal of Operational Research*, *184*(3), 946–961.
Jonnson, P., & Mattsson, S. -A. (2013). The value of sharing planning information in supply chains. *International Journal of Physical Distribution & Logistics Management*, *43*(4), 282–299.
Kang, Y., & Gershwin, S. B. (2005). Information inaccuracy in inventory systems: Stock loss and stockout. *IIE Transactions*, *37*(9), 843–859.
Kapoor, G., et al. (2009). Challenges associated with RFID tag implementations in supply chains. *European Journal of Information Systems*, *18*(6), 526–533.
Ketzenberg, M. E., Geismar, N., Metters, R., & van der Laan, E. (2012). The value of information for managing retail inventory remotely. *Production and Operations Management*, *22*(4), 811–825.
Kök, A. G., & Shang, K. H. (2014). Evaluation of cycle-count policies for supply chains with inventory inaccuracy and implications on RFID investments. *European Journal of Operational Research*, *237*(1), 91–105.
Kwak, J. K., & Gavirneri, S. (2014). Impact of information errors on supply chain performance. *Journal of the Operational Research Society*. doi:10.1057/jors.2013.175.
Lalwani, C. S., Disney, S. M., & Towill, D. R. (2006). Observable and controllable state space representations of a generalized Order-Up-To policy. *International Journal of Production Economics*, *101*(1), 173–184.
Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management Science*, *43*(4), 546–558.
Lee, H. L. (2010). Taming the bullwhip. *Journal of Supply Chain Management*, *46*(1), 1–7.
Lu, C. -C., Tsai, K. -M., & Chen, J. -H. (2012). Evaluation of manufacturing system redesign with multiple points of product differentiation. *International Journal of Production Research*, *50*(24), 7167–7180.
Machuca, J. A. D., & Barajas, R. P. (2004). The impact of electronic data interchange on reducing bullwhip effect and supply chain inventory costs. *Transportation Research Part E: Logistics and Transportation Review*, *40*(3), 209–228.
Mersereau, A. J. (2012). Information-sensitive replenishment when inventory records are inaccurate. *Production and Operations Management*, *22*(4), 792–810.
Metzger, C., Thiesse, F., Gershwin, S., & Fleisch, E. (2013). The impact of false-negative reads on the performance of RFID-based shelf inventory control policies. *Computers and Operations Research*, *40*(7), 1864–1873.
Min, H., & Zhou, G. (2002). Supply chain modeling: Past, present and future. *Computers & Industrial Engineering*, *43*(1–2), 231–249.
Miranda, P. A., & Garrido, R. A. (2009). Inventory service level optimization in distribution network design. *International Journal of Production Economics*, *122*(1), 276–285.
Montgomery, D.C., 2005. Design and analysis of experiments (6th ed.). Hoboken (New Jersey): John Wiley & Sons.
Mula, J., Campuzano-Bolarín, F., Díaz-Madroñero, M., & Carpio, K. M. (2013). A system dynamics model for the supply chain procurement transport problem: Comparing spreadsheets, fuzzy programming and simulation approaches. *International Journal of Production Research*, *51*(13), 4087–4104.

Nachtmann, H., Waller, M. A., & Rieske, D. W. (2010). The impact of point-of-sale data inaccuracy and inventory record data errors. *Journal of Business Logistics*, *31*(1), 149–158.

Qian, Y., Chen, J., Miao, L., & Zhang, J. (2012). Information sharing in a competitive supply chain with capacity constraint. *Flexible Services and Manufacturing Journal*, *24*(4), 549–574.

Raman, A., DeHoratius, N., & Ton, Z. (2001). Execution: The missing link in retail operations. *California Management Review*, *43*(3), 136–152.

Rekik, Y. (2011). Inventory inaccuracies in the wholesale supply chain. *International Journal of Production Economics*, *133*(1), 172–181.

Rekik, Y., & Sahin, E. (2012). Exploring inventory systems sensitive to shrinkage – Analysis of a periodic review inventory under a service level constraint. *International Journal of Production Research*, *50*(13), 3529–3546.

Rekik, Y., Sahin, E., & Dallery, Y. (2009). Inventory inaccuracy in retail stores due to theft: An analysis of the benefits of RFID. *International Journal of Production Economics*, *118*(1), 189–198.

Rekik, Y., Sahin, E., Jemai, Z., & Dallery, Y. (2008a). Execution errors in retail supply chains: Analysis of the case of misplaced products. *International Journal of Systems Science*, *39*(7), 727–740.

Rekik, Y., Sahin, E., & Dallery, Y. (2008b). Analysis of the impact of the RFID technology on reducing product misplacement errors at retail stores. *International Journal of Systems Science*, *39*(7), 727–740.

Rekik, Y., Jemai, Z., Sahin, E., & Dallery, Y. (2007). Improving the performance of retail stores subject to execution errors: Coordination versus RFID technology. *OR Spectrum*, *29*(4), 597–626.

Riddalls, C. E., Bennett, S., & Tipi, N. S. (2000). Modelling the dynamics of supply chains. *International Journal of Systems Science*, *31*(8), 969–976.

Sahin, E., Buzacott, J., & Dallery, Y. (2009). Analysis of a newsvendor which has errors in inventory data records. *European Journal of Operational Research*, *188*(2), 370–389.

Sahin, E., & Dallery, Y. (2009). Assessing the impact of inventory inaccuracies within a Newsvendor framework. *European Journal of Operational Research*, *197*(3), 1108–1118.

Sarac, A., Absi, N., & Dauzre-Prs, S. (2010). A literature review on the impact of RFID technologies on supply chain management. *International Journal of Production Economics*, *128*(1), 77–95.

Sari, K. (2008). Inventory inaccuracy and performance of collaborative supply chain practices. *Industrial Management and Data Systems*, *108*(4), 495–509.

Sarimveis, H., Patrinos, P., Tarantilis, C. D., & Kiranoudis, C. T. (2008). Dynamic modeling and control of supply chain systems: A review. *Computers and Operations Research*, *35*(11), 3530–3561.

Spiegler, V. L. M., & Naim, M. M. (2014). The impact of freight transport capacity limitations on supply chain dynamics. *International Journal of Logistics Research and Applications*, *17*(1), 64–88.

Sterman, J. D. (1989). Modelling managerial behavior: Misperceptions of feedback in a dynamic decision-making experiment. *Management Science*, *35*(3), 321–339.

Strozzi, F., Bosh, J., & Zaldivar, J. M. (2007). Beer game order policy optimization under changing customer demand. *Decision Support System*, *42*, 2153–2163.

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.

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, *52*(4), 802–815.

Thiel, D., Hovelaque, V., & Thi Le Hoa, V. (2010). Impact of inventory inaccuracy on service-level quality in (Q,R) continuous-review lost-sales inventory models. *International Journal of Production Economics*, *123*(2), 301–311.

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*, *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.

Uçkun, C., Karaesmen, F., & Savas, S. (2008). Investment in improved inventory accuracy in a decentralized supply chain. *International Journal of Production Economics*, *113*(13), 546–566.

Van Ackere, A, Larsen, E. R., & Morecroft, J. D. W. (1993). Systems thinking and business process redesign: An application to the beer game. *European Management Journal*, *11*(4), 412–423.

Wang, X., Disney, S. M., & Wang, J. (2012). Stability analysis of constrained inventory systems with transportation delay. *European Journal of Operational Research*, *223*(1), 86–95.

Wiengarten, F., Humphreys, P., McKittrick, A., & Fynes, B. (2013). Investigating the impact of e-business applications on supply chain collaboration in the German automotive industry. *International Journal of Operations and Production Management*, *33*(1), 25–48.

Wikner, J., Towill, D. R., & Naim, M. (1991). Smoothing supply chain dynamics. *International Journal of Production Economics*, *22*(3), 231–248.

Wright, D., & Yuan, X. (2008). Mitigating the bullwhip effect by ordering policies and forecasting methods. *International Journal of Production Economics*, *113*(2), 587–597.

Wong, C. W. Y., Lai, K. -H., Cheng, T. C. E., & Lun, Y. H. V. (2014). The role of IT-enabled collaborative decision making in inter-organizational information integration to improve customer service performance. *International Journal of Production Economics*. doi:10.1016/j.ijpe.2014.02.019.

Yuan, X., Shen, L., & Ashayeri, J. (2010). Dynamic simulation assessment of collaboration strategies to manage demand gap in high-tech product diffusion. *International Journal of Computer Integrated Manufacturing*, *25*(6), 647–657.

Xu, J., Jiang, W., Feng, G., & Tian, J. (2012). Comparing improvement strategies for inventory inaccuracy in a two-echelon supply chain. *European Journal of Operational Research*, *221*(1), 213–221.

Zhu, X., Mukhopadhyay, S. K., & Kurata, H. (2012). A review of RFID technology and its managerial applications in different industries. *Journal of Engineering and Technology Management*, *29*(1), 152–167.