The Effects of Bullwhip on Item Level Performance

Full Paper

Cesar Ayala
University of North Georgia
cayala@ung.edu

Gerard Burke
Georgia Southern University
gburke@georgiasouthern.edu

Geoffrey Dick
Georgia Southern University
geoffreydick@georgiasouthern.edu

Alan Mackelprang
Georgia Southern University
amackelprang@georgiasouthern.edu

Abstract

This research investigates how information and material distortions affect the inventory management performance of a major retailer. Bullwhip effects (BWEs) are individually calculated for dozens of products carried by dozens of retail locations. Relationships between item/store-level BWEs and item/store-level performance measures including gross margins and inventory levels are tested and reported.

Keywords: Bullwhip Effect, Inventory Management, Performance Measurement, Empirical Methods, Simultaneous System of Equations

Introduction

Inventory management decisions regarding levels of stock and timing of replenishment orders often seek to balance costs of having too much on-hand (overstocking) versus having too little (understocking). Overstocking costs include holding cost, shrinkage, markdowns and cost of capital. Understocking costs include lost sales, customers switching, store staff, store loyalty, and expedited shipping expenses.

To highlight the magnitude of the challenge faced by retailers, an inventory study on the global retail sector conducted by the IHL Group found that poor inventory management led to retailers losing over $818 billion in 2012 (Tyco 2012). According to IHL's study, 56% of the $818 billion was composed of inventory stockouts, while the remaining 44% was due to overstocking. IHL's study indicates that mismatched supply and demand are substantially detrimental to retailers' performance, resulting in lost sales or heavy discounting to dispose of surplus stocks. IHL's study indicates that these non-optimal inventory levels result in part due to a breakdown in organizational internal and external replenishment processes.

Managing inventory information and deliveries are a major operational challenge for firms as they try simultaneously to reduce costs and improve customer service. To put it in perspective, according to the US Census, inventory investment in the U.S. for all retailers amounts to $551 billion dollars while sales are $389 billion dollars for June 2014 (http://www.census.gov). Previous research has estimated inventory investment to represent 36% of total assets and 53% current assets (Gaur et al. 2005). Such a significant capital investment requires the close supervision of management. The research is relevant to the study of information systems as supply chain management systems may require the redevelopment and configuration of existing systems to ensure that management is able to control the outcome of the bullwhip effect. The research question for this study is: how does distortion in information flows and distortion in material deliveries affect inventory management performance of a major retailer?

Background

For many companies, especially those in the retail industry, capturing consumer demand accurately is vital to business management. Typically, organizations rely on demand forecasts for estimating future sales. Demand forecasts represent a critical input for production management and inventory management (Watson 1987; Gutierrez et al. 2008). A variety of techniques exist for the development of accurate forecasts. However, despite the use of appropriate forecasting techniques, most forecasts still contain errors (Mentzer & Moon 2004). Demand uncertainty can be defined as the level of confidence the buyer has in correctly estimating sales (Grover & Saeed 2007). According to Lee & Billington (1995), a number of studies have revealed that demand uncertainty resulting from forecast errors has been identified as a key source of inefficiency in the supply chain.

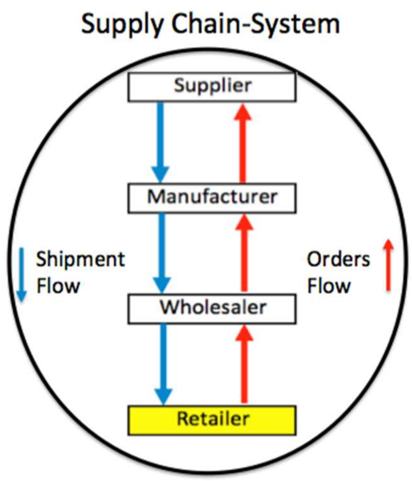

Figure 1: Supply Chain

At the inter-company level (Figure 1), demand uncertainty can move upward and have amplified supply chain ramifications. As flows of information and physical replenishments (Stevens 1989) move up and down the supply chain, they have the possibility to be perturbed or corrupted. One such possibility is the distortion in perceived demand information where practices across the supply chain create cascading effects. A particular and popularly discussed phenomenon of this type is the Bullwhip Effect (BWE). BWE exists when variability in demand information increases correspondingly as it is passed serially upstream from retailers to manufacturers. A small change in consumer demand can amplify and propagate into larger associated changes in upstream order variability (Chen et al. 2000). Classically, the BWE leads to cycles of stockouts and overstocking. Figure 2 provides a graphical representation of the inventory behavior of an item/store for a period of fifty one weeks based on the abnormal inventory growth calculation proposed by Chen et al. 2005, using a data item from this study.

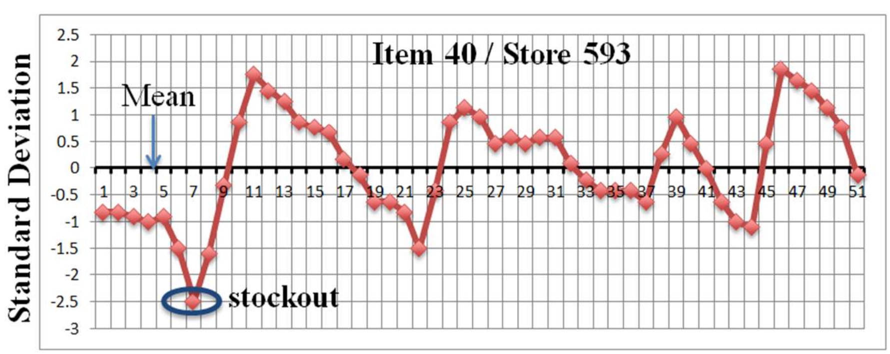

Figure 2: Item 40/Store 593 inventory behavior

The BWE can also occur in a downstream direction. Some have referred to the downstream directed bullwhip effect as the reverse bullwhip effect (RBWE) (Hull 2005; Özelkan & Çakanyıldırım 2009; Rong, Shen, Snyder 2009). The RBWE focuses on the material flow in the supply chain. The BWE-material distortion occurs when the variability of order receipts (shipments) is greater than variability in sales (Chen and Lee 2012). According to Chen & Lee (2012), BWE-information distortion is a source of BWE-material distortion.

It is Forrester's Industrial Dynamics (1958) that laid the groundwork for BWE research in supply chains. Forrester's theory of Industrial Dynamics captures the integrated nature and dynamic behavior of a network of interrelated organizations (Mentzer et al. 2001). The behavior of the system is a result of the interaction between the echelons in the supply chain network. The management of the system interaction between echelons identified by Forrester, represent a foundation for supply chain management research.

Table 1 below summarizes the sources of bullwhip identified in the literature. In addition it provides causes and remedies previously provided in the BWE literature.

Source	Cause	Remedy	Literature
Demand Signal Processing	Inventory planning based on orders instead of consumer demand	Information Sharing Investment in ERP's	Forrester (1958) Lee et al. (1997a) Chen & Lee (2012)
Order Lead-Time	Variability in Delivery	Lead-Time Reduction Speed up Delivery Faster order handling	Forrester (1958,1968) Metters (1997)
Order Batching	Production runs greater than average demand Economic batch quantities greater than average demand	Alignment of order batches with mean demand	Burbidge (1985; 1991) Disney & Towill (2003) Potter & Disney (2006)
Rationing & Gaming	Inventory Shortage	Balance inventories by developing an optimal Inventory level strategy	Houlihan (1988) Lee et al. (1997) Disney & Towill (2003)
Price Change	Effects of price changes	Stable Pricing Strategies (Everyday Low Price)	Fisher (1997) Lee et al. (1997a)
Behavioral	Systematic irrational behavior	Information sharing Investment in ERP's	Sterman (1989)

Table 1: Bullwhip Effect Sources and Remedies

Retailers are closest to actual consumer demand and therefore initiate sales triggers for various demand and supply planners across the supply chain networks. A retailer's store represents that part of the supply chain where sales of goods and services to the end-user takes place. Typically, a retailer's store demand plan is unconstrained, meaning it will not restrict its sales forecast due to a supply constraint. Often, materials flows or inventory replenishments of a retailer's stores are accomplished via a distribution center (DC). This research responds to calls from Cachon et al. (2007), Chen & Lee (2012) and Bray & Mendelson (2012) for additional empirical research to be conducted at more detailed units of analysis than industry and firm. Unlike previous empirical work, the unit of analysis in this study is the item/store level. This level of detail enables us to reduce cloudiness in relationships due to volume, product type and time. This research studies this portion of an actual retailer's supply chain. This supply chain structure is diagrammed in Figure 3.

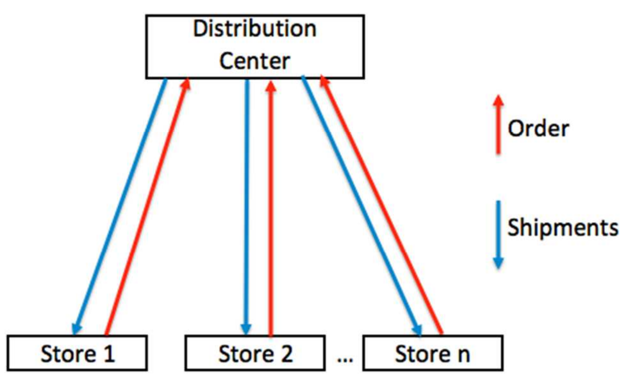

Figure 3: Retail Supply Chain Structure

Theoretical Foundation

Industrial Dynamics (Forrester 1958, 1961) suggests that amplification of order variance arises from the interaction between the components of a system. In a supply chain context, the supply chain network represents the system. The components of the systems are each individual echelon within the network: retailer, wholesaler, manufacturer and supplier. The behavior of the system, the supply chain network, is a result of the interaction between the echelons in the supply chain network. However, Forrester's theory of Industrial Dynamics lacks an explanation for how the amplification of orders manifests within each echelon. The "echelon" has to be studied as a subsystem within the supply chain network. This close-up view provides a more complete picture of the birth and immediate propagation of the BWE.

The theory of Organizational Information Processing (OIPT) provides us with a view of supply chain echelons as subtasks within a larger replenishment system (task). OITP views the organization as a network of interconnected informational subtasks (Galbraith 1973). Each of these subtasks is prone to various types of uncertainties (Galbraith 1973; Tushman & Nadler 1978). OIPT prescribes an organization's response for handling uncertainty under low and high conditions in order to bring stability to an organization subtask and minimize information and material distortions.

The Theory of Swift, Even Flow (TSEF) (Schmenner and Swink 1998), was developed as an explanatory framework for productivity gains in manufacturing settings. TSEF focuses on an organization's internal processes making them more productive by reducing waste. The integration of OIPT and TSEF is used to develop a holistic theory that links an organization's response to uncertainty and how these responses impact firm performance. Variability of interconnected processes is a common link between OIPT and TSEF. Based on TSEF, an organization establishes stability through the use of slack resources (buffer stock). The degree by which slack resources affect stability depends on the variability of the process; the higher the variability, the greater the need for additional slack resources. Although this framework explains an organization's response to uncertainty and its impact on operational performance, it does not explain why stockouts occur. Inventory Theory (IT) is a lens that can provide insight into this behavior of inventory systems.

IT operationalizes the various responses to uncertainty or variability prescribed by OITP and TSEF as it relates to an organization's inventory planning task. In the supply chain literature, inventory theory is used to refer to classical normative inventory models used by inventory planning systems (Rumyantsev & Netessine 2007; Olivares & Cachon 2009; Zipkin 2000; Eroglu & Hofer 2011a, b). Typically, an inventory planning system is driven by a set of parameters that captures aspects of economic consequence and management strategy (Porteus 2002). IT strives for profit maximization or cost minimization (Arrow et al. 1958). Stability of the demand and supply planning tasks of an organization are directly influenced by attaining inventory levels that meet established target service levels. A target service level is a parameter used by the inventory planning system to calculate inventory levels (Olivares & Cachon 2009).

At a macro level, Industrial Dynamics explains the behavior of a system as a result of interactions between the various system-components but falls short of explaining how management develops and executes their inventory strategy at a product level. To develop a general theory of an organizational response to amplification of information and material distortion, and its effect on inventory, this study integrates OIPT (Galbraith, 1973; Tushman & Nadler, 1978) and TSEF (Schmenner & Swink 1998; Schmenner 2004). OIPT focuses on stability of an organization's processes by adding buffers, whereas TSEF focuses on the productivity of a process with the focus on reducing waste by eliminating buffers. These two complimentary theories are integrated into a framework that provides a means for understanding both information distortion and material distortion constructs, incorporating stability and productivity into one theoretical lens. Incorporating these two theoretical lenses into our model reveals that an organizational drive for stability, coupled with the motive of productivity, leads to the sub-optimization of processes; often stability will sacrifice productivity. The variability of processes is what integrates both of these theories. The response to variability is what contrasts them. The integration of these two theories suggests that the response to dealing with variability is tightly coupled with the drive for stability and productivity. Finally, a return to IT explains how systemic inventory behaviors developed by managerial decision-making are processed through a planning system, controlling the level and change of inventory, to enhance inventory performance.

Hypothesis Development

This study categorizes the BWE into two dimensions: amplification of information distortion (BWI) and amplification of material distortion (BWM). Despite the ample amount of research in this area, there is a lack of studies examining BWE as two separate constructs and its impact on performance at the operational level (Cachon et al. 2007; Bray & Mendelson 2012; Chen & Lee 2012).

A supply chain is a system whose echelons are linked through two industrial flows: information flow and material flow. Stores place orders at distribution centers. This represents the information flow between a store and DC. The DC responds by fulfilling store orders. The fulfillment of the orders through delivery of the product represents the material flow between the DC and the store. An ideal scenario is one were information and material flows between the store and DC match; however, distortion in the flow of information prevents this from happening.

Ideally, orders placed by a store would match rate of sales (Mitchel 1923). Discrepancy between demand and orders lead to distortion in the flow of information. Store orders fluctuate as a result of several factors, which include variability in demand, order batching and lead-time. In addition, store orders tend to be more variable than demand due to ordering constraints such as minimum order quantities and economies of scale. Typically, orders placed by a store are constrained by pack-sized or minimum order quantities (Yan et al. 2009). This means that orders are placed in quantities that may be different to demand. In addition, stores take advantage of economies of scale by optimizing the load of product in a container.

The DC, having no visibility of store consumer demand, utilizes order realization as future predictors of demand (Lee et al. 1997a). A store order represents an input to the DC inventory capacity planning process. Stated differently, the information flow, manifested through the orders placed by the store, represent an input to the DC inventory capacity planning process. The quality of the plan depends largely on the information received. Distortion of the information received affects the capacity plan, which affects the material flow between the DC and the store. The material flow between the DC and store, is represented by the fulfillment of a store orders through the delivery of the product. Distortion in the flow of information, increases the likelihood a DC will fulfill a store orders at a later date, generating stockouts for the store. Also, fulfillment of past orders with current orders, reduces the inventory productivity of the store inventory by increasing the inventory levels to above normal. Thus, this study proposes the following hypothesis:

> **H1: Amplification of information distortions leads to amplification of material distortion.**

Within a retailer's intra-organizational perspective, the stores represent that echelon of the supply chain that is closest to the consumer. According to Lee et al. (1997a), retailers typically rely on demand realization as signals/predictors of future demand, which in turn is an input to a store ordering process and a key element in the management of inventory. Demand realization refers to historical sales, which are used in the development of a sales forecast for the placement of orders. Under-forecasting would lead demand to outstrip supply, creating stockouts; while over-forecasting increases the inventory level. Both of these situations lead to abnormal inventory levels.

According to OIPT, an organization's processes are susceptible to three types of uncertainty: task uncertainty, external uncertainty and interrelated uncertainty. In the case of a store's ordering process, demand uncertainty influences the orders coming out of stores. The demand uncertainty, described above represents the external uncertainty of the task. In the presence of high uncertainty, lack of information, OIPT advocates for the use of increase information processing requirements and that the logical responses to dealing with this situation are to either increase the information processing capacity or reduce the need to process information. Typically, in a retail environment, the use of slack resources (safety stock) is employed for mitigating the effects of demand uncertainty. At the operational level inventory theory explains how demand uncertainty perturb inventory. Demand variability, as a result of demand uncertainty, distorts orders. This means demand uncertainty distorts the information flow between the store and DC leading to placing orders that lead to abnormal inventory levels. Thus, this study proposes the following hypothesis:

H2: Amplification of information distortion leads to abnormal inventory levels

A store ordering process is influenced by what OIPT refers to as interdependence uncertainty. The uncertainty arises from the flow of information and flow of material between the store and the DC, resulting in a feedback loop problem. According to OIPT, this type of uncertainty occurs as a result of the lack of information between processes. Under perfect information, orders placed by the store should match orders delivered by the DC. This means there is a match between the information and material flows; however, distortion in the information flow would lead to a distortion in the material flow.

The TSEF provides additional insight into how distortion to the material flow leads to abnormal inventory levels. TSEF holds that a fast and even flow of materials or information within a process results in a more productive process; however, retailers are known for their significant inventory investment in slow selling items which are prone to have lumpy selling patterns, leading to higher forecast error. In addition, the store is relying on the distribution centers for fast replenishment; however, the lack of consumer demand information is a catalyst for stockouts at the distribution center, raising the probabilities of a stockout occurring in a backorder. Replenishing current orders with backorders causes a store to increase its inventory level above normal. Thus, this study proposes the following hypothesis:

H3: Amplification of material distortion leads to abnormal inventory levels

There is considerable literature supporting the link between operational performance and financial performance. Support for the link between operational performance and financial performance can be found in TSEF and Inventory Theory. A central premise of inventory theory is that operational performance explains financial performance (Eroglu & Hofer 2011a). This means there is a high degree of linkage between operational performance and financial performance. In addition, a good amount of empirical evidence exists in support of the link between operational performance and financial performance.

Gaur et al. (2005) provides empirical evidence regarding the direct relationship between inventory productivity and financial performance. Due to its close linkage, meaning its high predictive power, Gaur et al. (2005) developed a new inventory productivity metric called adjusted inventory turnover. While empirical evidence between bullwhip and firm performance is limited, there is some literature that provides empirical support. Metters (1997) attempts to estimate the impact of the BWE on supply chain performance and concludes that firm performance deteriorates due to increasing BWE. Results indicate that eliminating the BWE can increase the product profitability by 10% to 30%.

Capital investment increases as inventory level increases which leads to an increase in the operational cost. The competitive nature of a retail environment restricts retailers from increasing their prices. As inventory levels increase, so does the capital investment of an organization, reducing a product's gross margin. Based on the theories of swift, even flow, inventory theory, and the empirical results to date, the following hypothesis is proposed:

H4. Abnormal inventory levels leads to an increase in inventory investment, decreasing the profitability of a product.

This study also hypothesizes that operational performance partially mediates the relationship between BWE and financial performance. The BWE is an operational phenomenon that affects the financial performance. Support from this comes from the supply chain literature and TSEF:

H5. High amplification of information distortion leads to a decrease in gross margin.

H6. High amplification in material distortion leads to a decrease in gross margin.

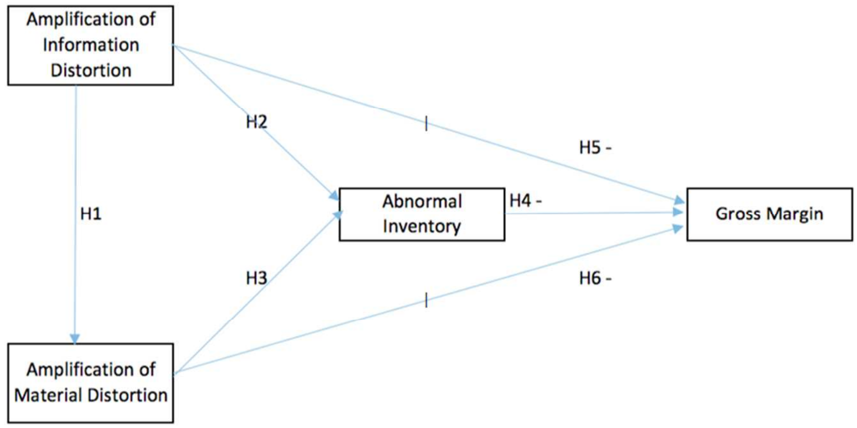

Figure 4: **Proposed Research Model**

Sample and Data Preparation

A large longitudinal dataset was obtained from a retail Fortune 500 company with the unit of analysis item/store, consisting of 2,051,967 observations (236 item * 211 Store * 53 weeks), of which 370,974 were used. Outlying data, data for which observations were not available for the whole time period, any negative observations and data relating to partial ship units were removed from the original data set. This ensures the integrity of the data used for generating the orders placed and orders received variables.

The first filter was rerun to ensure a balanced sample was obtained. Item/Store observations with greater than or equal to 53 observations after all applied filters were retained. Winsorizing the data was the final data preparation step. Winsorization of the data is a standard method used to diminish the presence of outliers (Chen et al. 2005). An outlier, for winsorization purposes, considers the values of the tails of the distribution as extreme (Barnett and Lewis 1994). By winsorizing the data, this study replaces the most extreme values with the cutoff established. A common cutoff for winsorizing the data is 1% of the highest and lowest values of the distribution tails, which is what this study followed. Descriptive statistics for all variables are presented in Table 2.

Variable	N	Mean	S.D.	Min	Max
Amplification of Information Distortion **(wbwi)**	370,974	1.589	5.737	-4.5	32
Amplification of Material Distortion **(wbwm)**	370,974	1.547	6.239	-4.5	40
Abnormal Inventory **(wabi)**	370,974	-0.010	0.965	-2.227	2.063
Gross Margin **(wgmr)**	370,974	0.116	0.205	0	0.631

Table 2: Descriptive statistics

Method

The model is a simultaneous equation system with one exogenous variable (BWE information distortion) and three endogenous variables (BWE material distortion, abnormal inventory and gross margin ratio) of which two of them are endogenous regressors (BWE material distortion and gross margin ratio)**.** Ordinary least-squares estimation of these equations will provide biased and inconsistent estimates of the parameters (Judge et al. 1985; Brush et al. 1999; Kennedy 2008; Wooldridge 2010).

The study utilizes simultaneous system of equations (SSE) to assess the model under investigation. Advantages of SSE consist of its ability to handle difficult data such as longitudinal with auto-correlated errors, multi-level data, non-normal data and incomplete data. SSE requires a well-defined model where variables that affect other variables and the directionalities of the effects are established as a priori. It is these a priori specifications that define hypotheses, and what makes up the model to be analyzed (Kline

2011). SSE allows us to obtain consistent estimation of the parameters; however, the standard errors still need to be adjusted.

Studies utilizing longitudinal data, such as the one used in this study, typically contain observations across multiple dimensions such as product, store, firm and time. In longitudinal studies or panel data, each unit is observed at several occasions over time. Longitudinal data are by definition clustered because multiple observations over time are nested within units, typically subjects (Rabe-Hesketh and Skrondal 2012). This means the standard assumption of independent observations is likely to be violated because of dependence among observations within the same cluster. To correct the standard errors of the estimates, this study clusters for time and store keeping unit (SKU). This requires the standard errors be adjusted for correlations across both of these dimensions. In this study this is achieved by taking the covariance estimator of clusters by time, plus the estimator that clusters by product minus the heteroskedasticity robust ordinary least square covariance matrix (Cameron, Gelbach & Miller 2006; Thompson 2011). This technique enables us to obtain standard errors that are robust for correlate along two dimensions.

This study decomposed the direct, indirect and total effects for each path following Sobel (1987), along with the standard errors obtained by the delta method for investigating the mediating effect of abnormal inventory levels between both BWE variables and financial performance. Stata is the statistical package utilized. The maximum likelihood algorithm is used for running the SEM module.

Model Development

A continuous variables model is used to examine the impact of amplification of information and material distortion on performance. Performance is captured through abnormal inventory growth and gross margin. This study begins with an equation where amplification of material distortion is a linear function of amplification of information distortion. The basis for this relationship comes from Chen & Lee (2012), where orders to suppliers tend to have larger variance than sales to buyers.

This study estimates the effect of both amplification variables on performance, while controlling for the endogenous or simultaneous influence of amplification of information distortion on material distortion. This is part of the reasoning for why a simultaneous system of equations is warranted for identifying, individually and collectively, the impact amplification of information and material distortions have on performance. Thus the model attempts to reflect the refined BWE theoretical foundation developed by Chen & Lee (2012). The subscripts i, j and t are used in the model to represent item/SKU, store, and time respectively.

The model uses the following variables, operationalizing the constructs:

- $wbwi_{ijt}$ - amplification of information distortion calculated as the winsorized Var [Order Quantity Placed] - Var [Sales Units]
- $wbwm_{ijt}$ - amplification of material distortion calculated as the winsorized Var [Order Quantity Received] - Var [Sales Units]
- $wabi_{ijt}$ – calculated as $(inventory\ days_{ijt})$ – $[(mean\ inventory_i)\ /\ SD\ invetory\ days_i]$
- $wgmr_{ijt} - gross\ margin_{ijt}\ /\ sales\ dollars_{ijt}$
- I_i – control variable for item (continuous variable)
  - Mean of I for each dependent variable (continuous variable)
- J_j– control variable for store (continuous variable)
  - Mean of J *for each* dependent variable (continuous variable)
- T_{ijt}– control variable for time (continuous variable)

The study begins with the equation for amplification of material distortion. This equation includes all three control variables (item, store and time). As previously discussed in the hypothesis development, amplification of material distortion is influenced by amplification of information distortion and is captured in this study as:

- $wbwm_{ijt} = \beta_1 wbwi_{ijt} + I_i + J_j + T_{ijt} + \varepsilon_{ijt}$

Hypothesis 1: Amplification of information distortion has a direct and positive influence on amplification of material distortion (coefficient β_1 > 0) after controlling for item, store, and time, and clustering around store and SKU.

The second set of hypotheses state that amplification distortion negatively impacts the inventory levels of products at an item store. The negative effect is captured by a positive effect on abnormal inventory, which means high inventory levels is due to the effect of the amplification distortion of both information and material. This equation includes all three control variables.

- $wabi_{ijt} = \beta_2 wbwi_{ijt} + \beta_3 wbwm_{ijt} + I_i + J_j + T_{ijt} + \varepsilon_{ijt}$

Hypotheses 2 and 3: Amplification of information and material distortion has a positive influence on abnormal inventory (coefficients $\beta_2 > 0$ & $\beta_3 > 0$) after controlling for item, store and time, and clustering around store and SKU.

The last set of hypotheses state that abnormal inventory and both amplification variables negatively impact gross margin. This equation includes all three control variables.

- $wgmr_{ijt} = \beta_4 wbwi_{ijt} + \beta_5 wbwm_{ijt} + \beta_6 wabi_{ijt} + I_i + J_j + T_{ijt} + \varepsilon_{ijt}$

Hypotheses 4, 5 & 6: Abnormal inventory, amplification of information and material distortion has a negative influence on gross margin (coefficients $\beta_4 < 0, \beta_5 < 0, \& \beta_6 < 0$) after controlling for item, store and time, and clustering around store and SKU.

The model was run with the filtered data described in the "Sample and Data Preparation" section. For triangulation purposes, the model was run with a subset of the filtered sample that contained only the positive values for the amplification variables. Table 3 provides the multicollinearity test. A violation of multicollinearity is assessed through the variance inflation factor (VIF) values. VIF results indicate there is no violation of multicollinearity.

Variable	wbwm	wabi	wgmr
wbwi	1.05	1.13	1.24
Stock Keeping Unit ***(I)***	1.04	1.03	1.04
Retail Store ***(J)***	1.00	1.03	1.01
Week ***(T)***	1.00	1.00	1.00
wbwm		1.13	1.32
wabi			1.18

Table 3: VIF – variance inflation factor

Empirical Results

Results indicate support for three of the hypothesis (see Table 4). Amplification of information distortion does not lead to higher abnormal inventory. A possible explanation for this is due to the batching effect experienced by items. In the case of information distortion, sales are not constrained by a ship-unit as orders are placed. When a store places an order, typically it orders more than it needs due to various factors such as ship-units and economies of scale. The indirect and total effect analysis indicate that for amplification of material distortion, there is only a direct effect, while for amplification information distortion, an indirect and direct effect exist (see Table 5). Perhaps, amplification of material distortion has a mediating effect between amplification of information distortion and abnormal inventory growth. Contrary to hypotheses 5 and 6, the BWE variables positively impacted gross margin. Based on previous research, a characteristic of slow selling items is their high margins. It may be that high amplification of material distortion produces an increase in gross margin as the two are related.

Dependent	Independent	Coefficients	z	Hypothesis
wbwm	wbwi	0.3391	10.43	H1 Supported
wabi	wbwi	-0.0455	-19.70	H2 Rejected
	wbwm	0.0599	24.70	H3 Supported
wgmr	wabi	-0.0396	-17.59	H4 Supported
	wbwi	0.0008	3.71	H5 Rejected
	wbwm	0.0017	10.66	H6 Rejected

Table 4: Path coefficients, z values and hypotheses

		Indirect Effects		Total Effects		Proportion of Total Effect Mediated
Dependent	Independent	Coefficients	z	Coefficients	z	
wabi	wbwi	0.0203	10.67	-0.0252	-8.24	0.8052
	wbwm	-	no path	0.0599	24.7	-
wgmr	wbwi	0.0016	10.11	0.0024	14.05	0.6626
	wbwm	-0.0024	-24.68	-0.0007	-4.38	3.5379

Table 5: Indirect Effects and Total Effects

Conclusions

This study provides evidence regarding the directionality of the amplification variables on inventory performance and the different impacts each of the amplification variables have on operational and financial performance.

It also suggests that, contrary to the BWE literature, amplification of material distortion cannot be used as a surrogate for amplification of information. In addition, post-estimation results regarding the direct, indirect and total effects provide evidence that amplification of material distortion may have a partial mediation effect between amplification of information distortion and inventory performance, thereby offering a more comprehensive understanding of the relationship between each of the amplification variables and its impact on performance at a more granular level. From a managerial perspective, it is important to understand that both amplification distortion variables, although related, are different. Understanding their differences would enable managers, in the development of inventory strategies, including strategies for the assessment of the suitability of existing information systems and the redesign and configuration of such systems that will enable them to address their respective characteristics, both individually and collectively. It suggests that investing in tools that allows stores to capture better demand signals would enable them to reduce distortion of material shipments.

This study examined the direct relationship amplification of information distortion and amplification of material distortion have on abnormal inventory. Examining BWE as two separate constructs and their impact on performance at the operational level, provides evidence that amplification of information distortion and amplification of material distortion should be considered as two related but different BWE concepts. This suggests that future studies need to be careful when conducting research that utilizes one of these concepts as a surrogate for the other, as they may yield different results.

Finally, this study investigates the direct relationship BWE has on operational performance (abnormal inventory levels) and financial performance (gross margin). Results indicate a positive direct relationship between operational performance and financial performance. However, more interestingly the results indicate an inverse relationship between BWE and financial performance (gross margin). A plausible explanation is the high margins on some of these products. Limitations to this study include the noise introduced by the level of data granularity and it being limited to one company with a subset of their data. Future research should look to replicate this study at higher echelons of the supply chain with the same level of data granularity. This will help provide additional evidence regarding the related, but distinct characteristics for each of the BWE concepts. It would also be interesting for future research to examine the mediating role amplification of material distortion has between amplification of information distortion and operational performance. Such research should help clarify amplification of material distortion relationship with amplification of information distortion. Similarly, at the operational level, it would be interestingly to examine the mediating role operational performance has between BWE and financial performance.

References

Arrow, K. J., Karlin, & Scarf. 1958. *Studies in the mathematical theory of inventory and production*. Stanford University Press.

Barnett, V., & Lewis, T. 1994. *Outliers in statistical data* (Vol. 3). Wiley New York.

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

Brush, T. H., Bromiley, P., & Hendrickx, M. 1999. The relative influence of industry and corporation on business segment performance: an alternative estimate. *Strategic Management Journal*, (*20*:6), pp. 519–547.

Burbidge, J. L. 1985. Production planning and control: a personal philosophy. *Computers in Industry*, (*6*:6), pp. 477–487.

Burbidge, J. L. 1991. Period batch control (PBC) with GT–the way forward from MRP. In *BPCIS Annual Conference, Birmingham*.

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

Cameron, A. C., & Miller, D. L. 2010. Robust inference with clustered data. *Handbook of Empirical Economics and Finance*, pp.1–28.

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

Chen, H., Frank, M. Z., & Wu, O. Q. 2005. What Actually Happened to the Inventories of American Companies Between 1981 and 2000? *Management Science*, (*51*:7), pp. 1015–1031.

Chen, L., & Lee, H. L. 2012. Bullwhip Effect Measurement and Its Implications. *Operations Research*, (*60*:4), pp. 771–784.

Disney, S. M., & Towill, D. R. 2003. On the bullwhip and inventory variance produced by an ordering policy. *Omega*, (*31*:3), pp. 157–167.

Eroglu, C., & Hofer, C. 2011a. Inventory Types and Firm Performance: Vector Autoregressive and Vector Error Correction Models. *Journal of Business Logistics*, (*32*:3), 227–239.

Eroglu, C., & Hofer, C. 2011b. Lean, leaner, too lean? The inventory-performance link revisited. *Journal of Operations Management*, (*29:*4), pp. 356–369.

Feng, Y., D'Amours, S., & Beauregard, R. 2010. Simulation and performance evaluation of partially and fully integrated sales and operations planning. *International Journal of Production Research*, (*48*:19), pp. 5859–5883.

Fisher, M. L. 1997. What Is the Right Supply Chain for Your Product? *Harvard Business Review*, (*75*:2), pp. 105–116.

Forrester, J. W. 1958. Industrial Dynamics. *Harvard Business Review*, (*36*:4), pp. 37–66.

Forrester, J. W. 1961. *Industrial dynamics* (Vol. 2). MIT press Cambridge, MA.

Forrester, J. W. 1968. Industrial dynamics—after the first decade. *Management Science*, (*14*:7), pp. 398–415.

Galbraith, J. R. 1973. *Designing complex organizations*. Addison-Wesley Longman Publishing Co., Inc.

Gaur, V., Fisher, M. L., & Raman, A. 2005. An econometric analysis of inventory turnover performance in retail services. *Management Science*, (*51*:2), pp. 181–194.

Grover, V., & Saeed, K. A. 2007. The Impact of Product, Market, and Relationship Characteristics on Interorganizational System Integration in Manufacturer Supplier Dyads. *Journal of Management Information Systems*, (*23*:4), pp. 185–216.

Gutierrez, R. S., Solis, A. O., & Mukhopadhyay, S. 2008. Lumpy demand forecasting using neural networks. *International Journal of Production Economics*, (*111*:2), pp. 409–420.

Houlihan JB. 1987. International supply chain management. International Journal of Physical Distribution and Materials Management, (17:2), pp. 51–66.

Hull, B. Z. 2005. Are supply (driven) chains forgotten? *International Journal of Logistics Management*, (*16*:2), pp. 218–236.

Judge, G. G., Griffiths, W. E., Hill, R. C., Lütkepohl, H., & Lee, T.-C. 1985. *The Theory and Practice of Econometrics* (2 edition). New York: Wiley.

Kennedy, P. 2008. *A Guide to Econometrics* (6 edition). Malden, MA: Wiley-Blackwell.

Kline, R. B. 2010. *Principles and Practice of Structural Equation Modeling, Third Edition* (3rd edition). New York: The Guilford Press.

Lee, H. L., & Billington, C. 1995. The evolution of supply-chain-management models and practice at Hewlett-Packard. *Interfaces*, (*25*:5), pp. 42–63.

Lee, H. L., Padmanabhan, V., & Whang, S. 1997a. Information distortion in a supply chain: the bullwhip effect. *Management Science*, (*43*:4),pp. 546–558.

Lee, H. L., Padmanabhan, V., & Whang, S. 1997b. The Bullwhip Effect In Supply Chains. *Sloan Management Review*, *38*(3), 93–102.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. 2001. Defining supply chain management. *Journal of Business Logistics*, (*22*:2), pp. 1–25.

Mentzer, J. T., & Moon, M. A. 2005. *Sales forecasting management: a demand management approach*. SAGE Publications, Incorporated.

Metters, R. 1997. Quantifying the bullwhip effect in supply chains. *Journal of Operations Management*, (*15*:2), pp. 89–100.

Mitchell, T. W. 1923. Competitive illusion as a cause of business cycles. *The Quarterly Journal of Economics*, (*38*:4), pp. 631–652.

Olivares, M., & Cachon, G. P. 2009. Competing retailers and inventory: An empirical investigation of General Motors' dealerships in isolated US markets. *Management Science*, (*55*:9), pp. 1586–1604.

Özelkan, E. C., & Çakanyıldırım, M. 200). Reverse bullwhip effect in pricing. *European Journal of Operational Research*, (*192*:1), pp. 302–312.

Porteus, E. 2002. *Foundations of Stochastic Inventory Theory* (1 edition). Stanford, Calif: Stanford Business Books.

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

Rabe-Hesketh, S., & Skrondal, A. 2012. *Multilevel and Longitudinal Modeling Using Stata, Volumes I and II, Third Edition* (3 edition). College Station, TX: Stata Press.

Rong, Y., Shen, Z.-J. M., & Snyder, L. V. 2009. The impact of ordering behavior on order-quantity variability: a study of forward and reverse bullwhip effects. *Flexible Services and Manufacturing Journal*, (*20:*1-2), pp. 95–124.

Rumyantsev, S., & Netessine, S. 2007. What can be learned from classical inventory models? A cross-industry exploratory investigation. *Manufacturing & Service Operations Management*, (*9*:4), pp. 409–429.

Schmenner, R. W. 2004. Service Businesses and Productivity. *Decision Sciences*, (*35*:3), pp. 333–347.

Schmenner, R. W., & Swink, M. L. 1998. On theory in operations management. *Journal of Operations Management*, (*17:*1), pp. 97–113.

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

Stevens, G. C. 1989. Integrating the supply chain. *International Journal of Physical Distribution & Logistics Management*, (*19*:8), pp. 3–8.

Sobel, M. E. 1987. Direct and Indirect Effects in Linear Structural Equation Models. *Sociological Methods & Research*, (*16*:1), pp. 155–176.

Thompson, S. B. 2011. Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics*, (*99*:1), pp. 1–10.

Tushman, M. L., & Nadler, D. A. 1978. Information Processing as an Integrating Concept in Organizational Design. *Academy of Management Review*, (*3*:3), pp. 613–624.

Tyco. 2012, May 10. Inventory Distortion An $800B Issue for Retailers Worldwide.pdf. Retrieved from http://tycoretailsolutions.com/Pages/Challenges.aspx?ItemId=5

Watson, R. B. 1987. The Effects of Demand-Forecast Fluctuations on Customer Service and Inventory Cost When Demand is Lumpy. *The Journal of the Operational Research Society*, (*38*:1), pp. 75.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*. MIT press.

Yan, X. S., Robb, D. J., & Silver, E. A. 2009. Inventory performance under pack size constraints and spatially-correlated demand. *International Journal of Production Economics*, (*117*:2), pp. 330–337.

Zipkin, P. H. 2000. *Foundations of inventory management* (Vol. 2). McGraw-Hill New York.